The Dissertation Committee for Max Tomasz Brozynski
certifies that this is the approved version of the following dissertation:

Operations Research Models of Technology Transitions and the Role of Policy Support

Committee:

Benjamin D. Leibowicz, Supervisor

James E. Bickel

John J. Hasenbein

Sheila Olmstead

Michael E. Webber

Operations Research Models of Technology Transitions and the Role of Policy Support

by

Max Tomasz Brozynski

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT AUSTIN

May 2020

Dedicated to my parents.

Acknowledgments

The completion of this dissertation would not have been possible without tremendous support from family, friends, and faculty. Words cannot express how grateful and happy I am to have them in my life, but I will try nevertheless.

First, I'd like to thank my family, who provided relentless encouragement and support when I needed it most. My struggle was their struggle, and my achievement is their achievement.

In German, doctoral advisor is translated as *Doktorvater*, literally *doctor father*, and that is how I describe Dr. Benjamin Leibowicz, whose friendship I will forever cherish. From the moment we began working together, I knew quite quickly that I had found a mentor, knowing full well this was rare and I was lucky. Not only did Dr. Leibowicz teach me how to write and think about research, but he also supported and encouraged me when the going got tough. I am extremely proud to be his first Ph.D. graduate.

I'd like to thank all members of the dissertation committee, whose commitment and dedication to this dissertation is appreciated. I am grateful for Dr. John Hasenbein's unparalled teaching and passion for mathematics. Dr. Eric Bickel's decision analysis course fundamentally changed the way I think about decision making and his no-nonsense perspective taught me how to think for myself and never stop asking questions. I admire Dr. Sheila Olmstead's inspiring work ethic and passion for research. And finally, I greatly appreciate Dr. Michael Webber's committment to this obligation despite being on leave from the university.

I owe a considerable debt of gratitude to Shelby, who was always there to listen – without response – while I tried to conceptualize some idea or talk through an error in my work. But above all, from day one, thank you for being there when it was hardest. Thank you for taking care of me, distracting me, and encouraging me.

Thank you to Ed, with whom late-night hour-long conversations were always a welcome respite. And thank you to Nick and Joe, the finest gentlemen and scholars I have the pleasure of calling friends.

Finally, I gratefully acknowledge funding received through the Thrust 2000 – Jeff Heller Endowed Graduate Fellowship in Engineering, which made this dissertation possible.

Operations Research Models of Technology Transitions and the Role of Policy Support

Publication No. ____________

Max Tomasz Brozynski, Ph.D.
The University of Texas at Austin, 2020

Supervisor: Benjamin D. Leibowicz

Technology exists to fulfill functions in society, and technological innovations are continuously proposed to fulfill a particular function more effectively than an incumbent technology. These innovations are disseminated through society in a process called technology diffusion, and may ultimately replace an incumbent system in what is known as a technology transition. Due to the complex and uncertain underlying processes of technology adoption and diffusion, technical systems are resistant to transition to possibly superior alternatives. To address market, systemic, and structural failures preventing a desired technology transition, a policymaker, or other motivated agent, may strategically intervene to stimulate or accelerate the diffusion process. The success or failure of such policy intervention carries crucial implications for climate change mitigation, healthcare advances, and any other aspect of society that technology touches. However, existing models of optimal technology policy design omit or otherwise offer crude representations of these underlying processes and are largely case-specific at the expense of gleaning generalizable insights. The goal of this dissertation is to advance the operations

research modeling of technology transitions and the role of policy support. Through a variety of powerful operations research methodologies and relevant case studies, the individual projects in this dissertation offer novel models of technology transitions and insights into real-world technology policy, especially in the energy and climate domain. The three core chapters of this dissertation begin with the development of an applied energy system optimization model to assess a real-world climate policy, then move on to present two novel theoretical models that yield more general, analytical insights into technology policy decision making.

Chapter 2 addresses the growing importance of cities in climate change mitigation with the development of an energy system optimization model for urban-scale decarbonization. Our optimization model determines the least-cost power and transportation technology pathways to achieve a policy goal of net-zero greenhouse gas emissions and is used to analyze the Community Climate Plan adopted by Austin, Texas. We find that the policy objective can be achieved at a modest 2.7% increase in net present power and transportation costs relative to business-as-usual. The optimal decarbonization pathway proceeds through two distinct stages, first reducing power sector emissions, then electrifying transportation. Solar PV expands in the long run with or without the climate plan based on favorable cost projections, but the policy causes wind to replace natural gas as a complement to solar PV. Our findings also highlight the substantial value of intelligently scheduled battery storage operations and electric vehicle charging.

While the energy system optimization model of Chapter 2 captures numerous decisions for a complex urban energy system, it carries limiting assumptions about how technology diffusion occurs and the role of a policymaker in supporting a technology transition. Addressing these larger questions motivates the project in Chapter 3, which describes the development of two stylized models of technology policy decision making under uncertainty. The first model is a Markov reward process (MRP) that represents policy interventions with one-time, upfront costs, while the second is a Markov decision process (MDP) that represents interventions with recurring costs. For each model, we derive analytical expressions for the policymaker's willingness to pay (WTP) to raise the probabilities of advancing a technology development or diffusion process at various stages and compare and contrast the behaviors of the MRP and MDP models. Most notably, our analytical findings elucidate how the different cost-accounting schemes and the possibility of regressing from a more advanced development or diffusion stage back to an earlier one affect the WTP. Then, we conduct numerical sensitivity analysis to explore how the optimal technology policy portfolio varies with certain parameters, and present a case study on lithium-ion batteries for electric vehicles to demonstrate the practical application of our model to technology policy decision making.

In Chapter 4, we narrow our focus on technology transitions to infrastructure-dependent technologies common in energy, transportation, and telecommunications systems. Policymakers seeking to promote the diffusion of infrastructure-dependent technologies are often confronted with the *chicken-and-egg* problem: consumers are reluctant to adopt the technology without adequate infrastructure available, and firms are reluctant to invest in infrastructure without a sufficient number of adopters. This chicken-and-egg problem can hinder the diffusion of new technologies and prolong the timeframe over which existing technological systems remain locked-in. In this paper, we formulate a stylized model of technology policy decision making from the perspective of a policymaker who seeks to stimulate the market penetration of an infrastructure-dependent technology. Our model is a bilevel optimization problem in which a policymaker (leader) maximizes net social benefits by setting the levels of two incentives: a subsidy for a profit-maximizing firm (follower) to invest in infrastructure that raises the benefit of adoption to consumers, and a direct subsidy for consumers to adopt the technology. We analytically derive the firm's optimal infrastructure investment response to the upper-level policy decisions, and show that the bilevel model is equivalent to a quadratic program. To bypass non-convexity, we develop a custom solution strategy based on decomposition, and find that it performs better than directly applying an off-the-shelf solver to the potentially non-convex problem. Finally, we present a case study on the diffusion of battery electric vehicles and obtain insights into how a policymaker should allocate resources to charging infrastructure and vehicle incentives.

The three projects of this dissertation employ operations research methods to model technology transitions and the role of policy support. While each captures a variety of phenomena affecting technology transitions and optimal technology policy decision making, there remain thought-provoking questions that future research can address. We conclude this dissertation with proposed research directions and contemplate the high-level, real-world implications of this work.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

> As we begin to understand complex systems, we begin to understand that we're part of an ever-changing, interlocking, non-linear, kaleidoscopic world.
>
> W. Brian Arthur

1.1 Purpose

Technology exists to fulfill functions in society, and technological innovations are continuously proposed to fulfill a particular function more effectively than an incumbent technology. These innovations are communicated through society in a process called technology diffusion, and may ultimately replace an incumbent technological system in what is known as a technology transition. Due to the complex and uncertain underlying processes of technology adoption and diffusion, technical systems are resistant to transition to possibly superior alternatives. To address market, systemic, and structural failures preventing a desired technology transition, a policymaker, or other motivated agent, may strategically intervene to stimulate or accelerate the diffusion process. The success or failure of such policy intervention carries crucial implications for climate change mitigation, healthcare advances, and any other aspect of society that technology touches. However, existing models of optimal technology policy design omit or otherwise offer crude representations of these underlying processes and are largely case-specific at the expense of gleaning generalizable insights. The goal of this dissertation is to advance the operations research modeling of technology transitions and the role of policy support. Through a variety of powerful operations research methodologies and relevant case studies, the individual projects in this dissertation offer novel models of technology transitions and insights into real-world technology policy, especially in the energy and climate domain. The three core chapters of this dissertation begin with the development of an applied energy system optimization model to assess a real-world climate policy, then move on to present two novel theoretical models that yield more general, analytical insights into technology policy decision making.

In this chapter, we begin with a survey of the study of technology transitions and then explore technology transitions in energy systems, or *energy transitions*. Not only are energy transitions highly relevant today, but they also provide a rich set of examples that aptly demonstrate the underlying processes of technology adoption and diffusion, the concepts of path-dependence and lock-in, and the efforts of policymakers to stimulate a technology transition. Furthermore, the case studies designed to illustrate the models developed in this dissertation belong to the energy domain. Indeed, Chapter 2 explores an energy transition in electricity generation and transportation technologies to meet emissions reduction goals; Chapter 3 explores the development of lithium-ion batteries for electric vehicles; and Chapter 4 explores the diffusion of electric vehicles and their associated charging point infrastructure. While the model developed in Chapter 2 is specifically designed to study an energy transition, we stress that the models in Chapters 3 and 4 are general enough to describe technology transitions in many domains. Finally, as complementary to the more specific and technical literature reviews in the individual chapters, we summarize the extant research on technology transitions and the design of technology policy.

1.2 Definitions

At this point in the chapter, we find it useful to concisely define and compare the concepts of *technology adoption*, *technology diffusion*, and *technology transition*, especially since the concepts are certainly related, but nevertheless distinct, and will be used repeatedly throughout the dissertation. Technology adoption describes the "decisions to make full use of an innovation as the best course of action available" (Rogers, 1962). Research on technology adoption usually focuses on questions about what determines the timing of an adoption decision or whether or not an individual adopts at all. On the other hand, technology diffusion describes the "process in which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 1962). Therefore, models of technology diffusion explore aggregate phenomena, possibly over time, that result from adoption decisions and the economic and social interactions among firms, households, and policymakers. Widening the lens further, a technology transition is a "major technological transformation in the way societal functions ... are fulfilled," which not only involves technological changes, but also changes in user practices, regulation, infrastructure, and symbolic meaning (Geels, 2002). Typically, technology transitions refer to such shifts in large technological systems (Hughes, 2012). In short, technology transitions occur when one socio-technical system is replaced by another. We use the term-of-art *socio-technical* since the system comprises not only the technologies' characteristics, but also both physical and non-physical artifacts fundamental to the system.

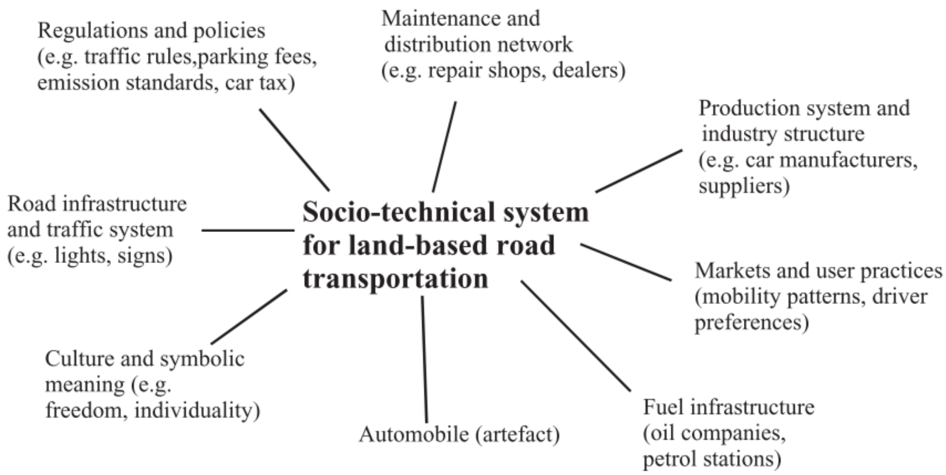

Figure 1.1. From Geels (2005), "Sociotechnical system for modern car-based transportation."

For example, the socio-technical system of road transportation is illustrated in Figure 1.1. The *potential* reconfiguration of technology, user practices, laws and regulations, and infrastructure necessary to accommodate sustainable transportation technologies such as electric or fuel-cell vehicles is a canonical example of a technology transition: away from the current petroleum-based socio-technical system of transportation towards something cleaner and more sustainable. Clearly, this transition would not be straightforward, and in examining Figure 1.1, we can hypothesize several barriers to transition for alternative fuel vehicles, namely high cost (relative to internal combustion engine vehicles), mismatch with consumer preferences (e.g., range anxiety and cultural meaning), and the chicken-and-egg problem (does fuel infrastructure or vehicle adoption come first?) (van Bree et al., 2010). In the chicken-and-egg problem, consumers are reluctant to adopt the technology without adequate infrastructure available, and firms are reluctant to invest in infrastructure without a sufficient number of adopters. In fact, in Chapter 4, we develop a bilevel optimization model that determines how a policymaker can overcome the chicken-and-egg problem. While the conceptual boundaries of technology adoption, diffusion, and transition are frequently blurred, the study of technology transitions more precisely deals with the competition between and replacement or evolution of technological systems.

1.3 A brief history of technology transitions research

In most surveys of the history of technological innovation research, Joseph Schumpeter, an Austrian-school political economist, doubtless begins the discussion (Stoneman, 2002). Indeed, Schumpeter first contemplated the role of technological progress in affecting economic growth and initiated the economic research tradition of studying the relationship between market structure and firms' innovative activity and performance (Cohen, 2015). He theorized that innovations are combinations developed within an economy and built on the existing stock of knowledge, leading to *creative destruction* in which markets reorient and redesign themselves during the relentless process of disruptive innovation (Schumpeter, 1939). Similarly, Solow (1957) indicated that technological innovation, having been largely ignored in economic research, was as important to economic growth as were capital and labor. However, it was not until mid-century, long before the term *technology transition* existed, that quantitative studies of technology diffusion began. In fact, it was the pioneering work of sociologists and anthropologists that kick-started the empirical research on technology adoption and diffusion. For example, Ryan and

Gross (1943)'s study of the diffusion of hybrid seed corn among farmers in Iowa and Coleman et al. (1957)'s study of the diffusion of a new drug among prescribing physicians remain canonical examples of diffusion research. While limited to the statistical analysis of survey data, these seminal works helped inspire technology diffusion concepts and terms such as logistic S-curves, innovator adopters, increasing returns, positive reinforcement, and network effects that remain in use today. Rogers (1962)'s *Diffusion of Innovations* summarized the research typologies and distilled from numerous studies common adoption and diffusion phenomena. For example, empirical findings frequently indicated that cumulative adoption against time follows an S-shaped curve, adopters are heterogeneous with respect to their degree of innovativeness and so can be categorized, and social networks play a crucial role in adoption decisions. Further, chance events, bad luck, and miscommunications have all been observed in adoption and diffusion processes.

Beyond these early empirical studies, two broad research streams have emerged to understand technology transitions. These research efforts are not merely the statistical manipulation and collection of data, but an attempt to *model* the reality. The first stream is a *quantitative* operations research and economics tradition that seeks to construct stylized, theoretical models of technology adoption and diffusion. In fact, a relatively modern approach to economics in general, called *complexity economics*, folds these theoretical results into a larger non-equilibrium perspective, which purports that the economy drives and emerges from the development of technology in an incessant feedback loop (Arthur, 2014). We consider this stream of research important because, first, it marks a departure from exclusively empirical studies. Second, observed phenomena receive rigorous mathematical treatment, and so their interactions generate theoretical insights. And third, it incorporates decision making. The second stream, from the sociology of technology tradition, develops *qualitative* frameworks for understanding technology transitions and evolution in large technical systems. This work was motivated in part by the recent and relevant focus on how sustainable energy transitions can occur, but nevertheless remains independent of any particular application or domain. Not only do we believe these two research streams to be complementary, but we also believe it crucial that future work meld these ideas and perspectives. Indeed, future research ought to apply the ideas of the latter to advance the former, thereby uniting the two research traditions. To that end, in Chapter 5, we examine how future research trajectories could accomplish this goal and which research questions remain largely unanswered.

As an early example of diffusion models in the operations research literature, the Bass Model (Bass, 1969) represented the diffusion process of a technology for which the rate of adoption among agents who have not yet adopted is a linear function of the number of previous adopters.[1] Its formulation reflects the distinction between *innovator adopters* who are self-motivated to choose a new technology, and *imitator adopters* who are encouraged to adopt by their observations of others who have already done so. The model was therefore an initial step in encoding the empirically-observed phenomena of social networks and information gathering at a theoretical level. Bass showed that his model fit the observed diffusion processes of many consumer

[1]Technically, Frank Bass's work fell under a marketing or management science umbrella. Indeed, much of the earlier research on technology adoption was motivated by business questions. For example, Coleman et al. (1957)'s study was funded by a large pharmaceutical company which sought to understand whether or not its drug advertisements in medical journals were effective.

durables, and a number of extensions to the Bass Model have since been proposed (Jiang and Jain, 2012; Niu, 2006; Norton and Bass, 1987). While Bass (1969) describes the aggregate behavior of his model as being driven by probabilistic adoption decisions at the individual level, his model is ultimately a deterministic one. The formal analysis of technological change as a stochastic process was really initiated by W. Brian Arthur, whose widely cited top-down models feature uncertainty in the technology transition pathway, such as how market shares will evolve. Incorporating uncertainty into diffusion processes marked a major step forward in the research. While uncertainty cannot be directly and completely observed in diffusion processes (i.e., we can only see what happened, not what *could have* happened), it provided an explanation for why some technologies diffused and others did not. For example, David (1985)'s famous case study of the QWERTY keyboard demonstrated how society can become *locked-in* to inferior technological regimes due to chance events that get amplified by *increasing returns*. Increasing returns, or positive feedback mechanisms, describe the phenomenon wherein benefits of the technology increase in the number of previous adopters.[2] For example, computer operating systems reveal increasing returns in that if one system gets ahead, i.e., establishes considerable market share, it will be adopted by more hardware manufacturers and will attract more compatible software, in turn increasing its market share, and so on. Increasing returns, therefore, is a catch-all phenomenon due to, among others, network effects, learning-by-using, learning-by-doing, and associated infrastructure investment feedback

[2]Increasing returns need not be an exclusively economic idea. From Matthew 25:29, "For to every one who has will more be given, and he will have abundance; but from him who has not, even what he has will be taken away." Finding an example of increasing returns in every aspect of life will come quite easily to the reader.

loops. Arthur's work theoretically demonstrated the consequences for trying to predict technological outcomes or ensure economic efficiency under increasing returns in a stochastic diffusion process in a way that complemented existing case studies. Arthur et al. (1987) modeled technological competition as a nonlinear (stochastic) Polya process, whereby the probability of adoption is an arbitrary function of the number of previous adopters.[3] The authors prove that the market shares in a nonlinear Polya process will eventually converge to a stable fixed point of the urn function, as is the case in the standard Polya model. Arthur (1989) modeled the diffusion process of a technology by a sequence of adoption decisions made by two types of agents. This research showed that under increasing returns, technological outcomes cannot be predicted ex-ante and an economically efficient market outcome cannot be guaranteed. The evolution of the market is non-ergodic in that small chance events tip the allocation toward one dominated by a single technology, instead of being averaged away. We call this *path-dependence*. Furthermore, there is a risk of becoming locked-in to a technology pathway with inferior long-run benefits if there is an early streak of agents who prefer an initially appealing but slow-to-improve technology. Most importantly, the consequences of increasing returns both motivate technology policy and indicate how important it is to design *intelligent* technology policy.

The concepts of path-dependence and technological lock-in have inspired numerous case studies, whose insights researchers have distilled into broader, qualitative frameworks for understanding technology transitions. Furthermore, the recent focus on sustainable energy transitions to mitigate climate

[3]In the standard Polya process, an urn contains some number of white and black balls. In each step of the process, a ball is removed and placed back in the urn with an outside ball of the same color.

change has led researchers to leverage case studies and qualitative frameworks to gather insights on designing technology policies to stimulate and accelerate these transitions. A number of collaborative Dutch researchers have developed the *multi-level perspective* (MLP) (Geels, 2002, 2005; Kemp, 1994; Kemp et al., 2001), which offers a typology by which technology transitions tend to occur. It distinguishes three interacting levels: niches, socio-technical regimes, and an exogenous socio-technical landscape. The socio-technical regime is characterized by path-dependence and stability, which are represented in three constituent parts: the socio-technical system, actors, and rules. Systemic developments in the socio-technical landscape are beyond the influence of the regime and are slow to change. When the existing socio-technical regime is replaced by another, a technology transition occurs. Radical innovations, i.e., innovations which are incompatible with the existing socio-technical regime, incubate in niches. In these niches, innovations enjoy protection from market selection and allow the opportunity for the innovation to deviate from the "rules" of the regime, experiment, and learn. Simultaneous pressure on the regime at the landscape level helps induce a technology transition. The three levels and their interactions are illustrated in Figure 1.2. For example, Geels (2002) explains how early steamships, while inferior to sailing ships, were adopted by the British Empire's subsidized mail service, which provided opportunities for technological development they would not have otherwise enjoyed. In the following section, we discuss the most popular technology transition to research – the energy transition. The historical record of energy transitions demonstrates the ideas of path-dependence and lock-in and the difficulty of designing technology policy.

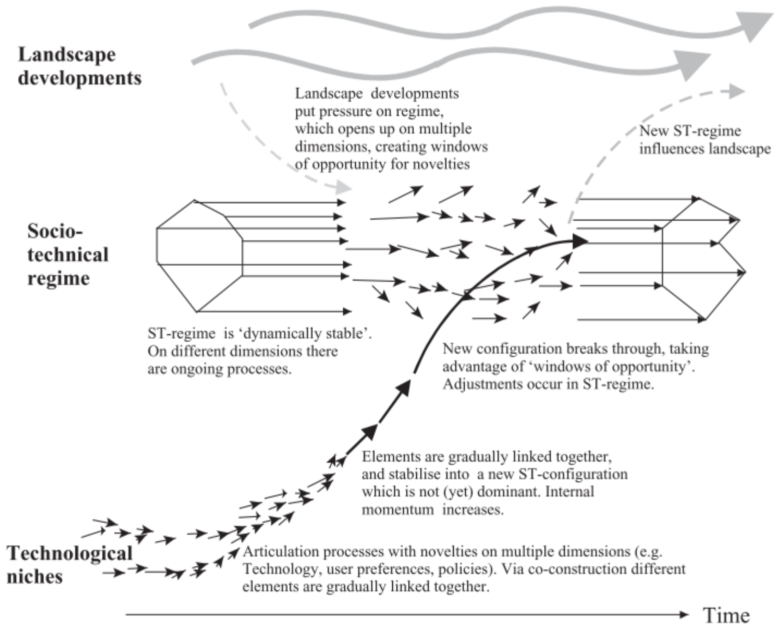

Figure 1.2. From Geels (2002), "A dynamic multi-level perspective on system innovations."

1.4 Energy transitions

The genesis of and motivation for this dissertation began with research questions arising out of a model of an urban-scale energy system developed in Chapter 2. To briefly introduce what an energy system is opens a proverbial can of worms. It can be difficult to draw the boundaries of this system, since it could be argued that all human activity is driven by the conversion of energy. However, when we talk about the energy system, especially in the context of energy transitions, we typically refer to the technologies and processes used to supply energy resources (e.g., oil, natural gas), convert energy from one form into another (e.g., electricity generation), and satisfy final demands for energy, goods, and services (e.g., space heating, transportation, food). More broadly, the energy system includes decision making agents such as policymakers, consumers, and firms, as well as institutions, behaviors, and norms. It is our largest and most complex socio-technical system; in fact, it is a system of socio-technical systems. In this section, we briefly discuss the motivations for studying energy transitions and provide a few examples that demonstrate the opportunity for advanced modeling approaches and techniques.

While the availability of cheap and reliable energy appears to be a fundamental driver of economic prosperity (Fouquet, 2016b), fossil fuels globally comprise about 80-85% of global primary energy sources (IEA, 2020; Smil, 2016), the combustion of which is responsible for about 78% of the increase in anthropogenic greenhouse gas emissions (IPCC, 2014). Researching historical energy transitions has become an avenue through which we might design climate policy to accelerate transitions to more sustainable energy systems (Fouquet, 2016a; Grubler, 2012; Grubler and Wilson, 2013; Smil, 2016). Fundamentally, researchers have generally agreed that while specific energy technology transitions at a national scale have occurred in just a few years, energy transitions remain slow at the global level. It has been suggested that these protracted transitions are due to carbon lock-in (Fouquet, 2016b; Seto et al., 2016; Unruh, 2000), wherein, through increasing returns effects such as scale economies, learning economies, adaptive expectations, and network economies, fossil fuel energy technologies are deeply entrenched in our energy systems and remain resistant to change. Seto et al. (2016) identify three main types of carbon lock-in: 1) infrastructural and technological, 2) institutional, and 3) behavioral. Ultimately, understanding these lock-in barriers is key to designing policy that effectively unlocks the system. To illustrate this, take, for example, battery electric vehicles, which promise to be an effective decarbonization technology for land-based transportation. First, on the one hand, petroleum-based vehicles currently enjoy substantial infrastructure, characterized by high sunk capital costs (highways, gas stations, etc.), remain cheaper than electric vehicles, and negative externalities of vehicle emissions are not priced; on the other hand, a substantial, capital-intensive charging infrastructure is needed to support diffusion of electric vehicles. And second, social norms and biased psychological decision making processes would need to be overturned for rapid adoption of electric vehicles. By no means a comprehensive list, these numerous lock-in effects imply designing policy to stimulate a transition can be daunting. Indeed, which barrier to transition should be targeted and by what means should it be targeted?

The difficulty of designing technology policies is borne out by the erratic historical record. Some past government campaigns to promote technology transitions have been lauded as tremendous successes, such as the swift adoption of hybrid seed corn driven by agricultural extension agencies in the U.S. (Griliches, 1957), or the creation of a leading wind turbine industry in Denmark (Klaassen et al., 2005). On the other hand, there have been a number of very expensive failures, including the U.S. Synthetic Fuels Corporation established to reduce dependence on imported fossil fuels during the oil crisis (Anadon and Nemet, 2014), or the French effort to deploy fast breeder nuclear reactors (Grubler, 2012). In recent history, Germany's *Energiewende*, a federal plan to reduce greenhouse gas emissions by 80-95% of 1990 levels and achieve 60% renewable electricity generation by 2050, while phasing-out nuclear power has stumbled (Morris and Jungjohann, 2016). Indeed, between 2000 and 2015 low-quality lignite coal consumption increased and natural gas (comparatively much cleaner) consumption fell, largely to offset low capacity factors of solar and wind electricity generation (11% and 17%, respectively) (IEA, 2020; Smil, 2016). While emissions did in fact fall 12%, this is likely because the overall primary energy use decreased; indeed, neighboring countries without such an *Energiewende* saw 18% reductions in emissions (Smil, 2016).

In the transportation domain, technology policy has been equally erratic. For example, in 2012, Denmark provided approximately $33,000 in total electric vehicle subsidies per vehicle, but electric vehicles made up less than 0.5% of market share (Sierzchula et al., 2014). In Norway, however, electric vehicles enjoyed about 3% market share with only $15,000 in subsidies. Clearly, financial incentives are not necessarily sufficient to induce widespread adoption, and other factors could be equally or even more important drivers. These energy transition examples serve to illustrate the complexity of designing optimal technology policy. Indeed, while the qualitative frameworks for understanding technology transitions and historical case studies are helpful in painting a fuller picture, modeling approaches consistently fail to capture key phenomena or offer practical decision support.

In Chapter 2 we apply an urban-scale energy system optimization model to identify the least-cost energy transition that meets exogenous emissions targets. This energy transition is essentially a temporal series of operational and investment decision for electricity generation and transportation technologies. While the work generates patterns and insights, indicating where a policymaker ought to focus decarbonization efforts, methodological assumptions and limitations mean that certain aspects of technology adoption and diffusion are not captured. For example, once a technology becomes cost-effective in the model, it is adopted. These limitations have inspired a closer, theoretical perspective of technology transitions that the remaining chapters address.

1.5 The role of policy support

Many governments aim to promote the development and diffusion of new technologies such as renewable energy sources, medical treatments, agricultural innovations, and alternative fuel vehicles. Economic theory generally suggests that government intervention is justified in cases of market failure, including externalities and informational asymmetry. In the more specific context of policy support for new technologies, Salmenkaita and Salo (2002) summarize four key policy rationales: market failure (under-investment in research and development (R&D) because firms are unable to capture all the benefits of innovation, so private benefits are smaller than social benefits), systemic failure (coordination problems among R&D players with different incentives), structural inertia (path-dependence and feedbacks hamper the pursuit of new technologies), and anticipatory myopia (information about future opportunities is expensive to acquire, leading to under-investment). Technology policy is also viewed as a means of addressing negative externalities that often go unpriced in the market, such as greenhouse gas emissions that cause climate change (Nemet and Kammen, 2007).

Technology policy, to provide a definition, is the both financial and non-financial exercise of a policymaker to affect technological change, and it comes in many forms. Instruments that directly target technologies include public R&D funding and adoption subsidies to stimulate supply and demand side innovation, respectively. More general policies like carbon taxes, cap-and-trade, and renewable portfolio standards do not target a specific technology, but rather can lead to *induced innovation* by mandating or raising the incentives for innovation in a sector of the economy. For example, in Chapter 2 we specifically consider a quantity constraint on GHG emissions which induces a change in the power generation mix and vehicle fleet; and in Chapter 4, we consider a combination of infrastructure investment and adoption subsidies to directly stimulate adoption of electric vehicles.

To address these failures preventing a desired technology transition, a policymaker, or other motivated agent, may strategically intervene in the diffusion process. The success or failure of such policy intervention carries crucial implications for climate change mitigation, healthcare advances, and any other aspect of society that technology touches. However, the extant research on designing optimal technology policy is insufficient. While empirical case studies and qualitative conceptualizations have advanced our understanding of technology transitions, they have limited relevance as guides for making technology policy decisions. They rely on an inductive logic that attempts to establish qualitative, policy-relevant insights through the synthesis of case studies of specific experiences across myriad application domains and contexts. Indeed, poorly designed technology policy, intending to correct a market or systemic failure, may instead create a government failure, in which case the intervention actually causes further economic inefficiency (Stiglitz, 2009). The literature largely lacks a quantitative, theoretical modeling framework capable of yielding generalizable guidance for technology policy decisions. This dissertation addresses this research gap.

1.6 Modeling approaches for designing technology policy

In this section, we provide a brief overview of operations research modeling approaches for designing technology policy that is intended to complement the more technical presentation in the individual chapters. Our survey proceeds through the methodologies as they are presented in the core chapters of the dissertation.

First, however, it is worthwhile to remark on the application of operations research models for technology transitions. As we have described above, technology transitions involve heterogeneous decision makers with different objectives; complex technological, economic, and social interactions among these decision makers; and fundamental uncertainty. Operations researchers have available to them a suite of methodologies that alone, or in combination, serve as powerful modeling tools. For example, in Chapter 2 we develop a large-scale linear program involving thousands of decision variables. In Chapter 3 we employ Markov decision and reward processes to model the uncertain development or diffusion of a technology that incorporates technology policy decision making. And in Chapter 4, we explore how a policymaker can overcome the chicken-and-egg problem by formulating a bilevel optimization (or sequential game) model.

1.6.1 Energy system optimization models

As discussed above, the urgent need to address climate change and curb anthropogenic emissions has spurred recent work in developing theories of technology transitions. To address climate change and identify reasonable mitigation strategies, a thorough understanding of energy systems is necessary. To that end, energy systems models exist to generate a range of insights and analyses on the supply and demand of energy and have enjoyed much research attention in the last half-century. Pfenninger et al. (2014) distinguish four energy system modeling paradigms: 1) energy system optimization models,

2) energy system simulation models, 3) power systems and electricity market models, and 4) qualitative and mixed-method scenarios. In this section, we focus on energy system optimization models. The sheer complexity of energy systems is well suited to modeling by large-scale operations research modeling paradigms, including linear, mixed-integer, and stochastic programs, especially with growing computing power and intense data collection and forecasting. Usually applied on the national or global scale, these models contain detailed, bottom-up representations of the technological components that constitute an energy system. They are used to explore how energy systems are likely to evolve – or should ideally evolve – over some specified timeframe, depending on techno-economic assumptions and policy settings.

An evolution of the energy system is known as a transformation pathway, defined by the collection of all technology investments and operational decisions. Should the transformation pathway represent a fundamental shift in the energy system, we would refer to this as an energy transition. Energy system optimization models are typically constructed to identify the least-cost transformation pathway that satisfies all energy demands as well as a host of other constraints. By introducing additional parameters or constraints, energy system optimization models can be used to analyze a range of energy and climate policies. Specific questions that they intend to answer include: 1) Is it possible to achieve an emissions target given available technologies and constraints on their deployment? 2) What is the economic cost of achieving a climate policy goal? 3) What technological transformation pathway allows a policy goal to be accomplished most cost-effectively? Well-known optimization frameworks include the MARKAL/TIMES family (Loulou et al., 2004; Loulou and Labriet, 2007; Loulou, 2007), MESSAGE (Messner and Strubegger, 1995;

Messner and Schrattenholzer, 2000), and OSeMOSYS (Howells et al., 2011).

Chapter 2 addresses the growing importance of cities in climate change mitigation with the development of an energy system optimization model for urban-scale decarbonization. Our optimization model determines the least-cost power and transportation technology pathways to achieve a policy goal of net-zero greenhouse gas emissions and is used to analyze the Community Climate Plan adopted by Austin, Texas. Our approach to energy system optimization is novel in that we are able to capture the synergies between power and transportation. The power and transportation sectors are the two largest GHG emitters in the U.S., accounting for 28% and 29% of total emissions, respectively (EPA, 2017b), and evidence suggests that these shares are even higher in urban areas. Any serious effort to decarbonize cities will therefore require monumental changes in how we generate electricity and travel from place to place. At present, transportation and power are largely decoupled, at least in the U.S. Petroleum products dominate the fuel mix of the former, but have been almost completely phased out of the latter. This situation is likely to change in the future as transportation shifts to alternative fuels that are more closely linked to the power sector, especially under climate policies (Anandarajah et al., 2013; Bosetti and Longden, 2013; Edelenbosch et al., 2017; Pietzcker et al., 2014). Amid this trend, powerful synergies will emerge whereby mitigation activities in power and transportation mutually enhance one another. We design our model to leverage these synergies while optimizing decarbonization pathways.

One such synergy arises with the use of electricity as a transportation fuel. Powering transportation with electricty causes larger marginal GHG emissions reductions as the power sector decarbonizes upstream.[4] This is one reason why most energy-economy models choose to decarbonize electricity generation before investing significantly to convert transportation fleets to electric vehicles (Löffler et al., 2017; Pietzcker et al., 2014). Electrification of transportation would increase overall demand levels in the power sector, necessitating greater capacity utilization and/or additional capacity investments. Hydrogen fuel cell vehicles can also provide carbon-free transportation if hydrogen is produced via electrolysis using renewable electricity (Anandarajah et al., 2013). So, the hydrogen route to sustainable mobility is also enhanced by decarbonizing the power sector.

In the reverse direction, uptake of alternative fuel vehicles facilitates the integration of intermittent renewables into the power sector and provides valuable services to the electric grid. Electric vehicle charging can be managed as a flexible load to absorb renewable electricity during periods of excess supply. Choi et al. (2013) demonstrate that intelligently scheduling electric vehicle charging reduces the cost of complying with a renewable electricity standard in the power sector. Hydrogen production via electrolysis can similarly be considered a flexible load, occurring when renewable energy is abundant to provide fuel for hydrogen-based vehicles. In a vehicle-to-grid (V2G) system, electric vehicle batteries are capable of supplying power to the grid at times of peak demand or low renewable resource availability. With widespread adoption of electric vehicles, V2G could encourage further deployment of renewable technologies and reduce investments in peaking power plants or stand-alone

[4]Norway has historically dominated electric vehicle per-capita adoption, *and* its electricity generation mix is nearly 100% hydroelectric. On the other hand, while China leads absolute electric vehicle adoption, nearly half of its electricity is generated by coal plants.

energy storage technologies (Nunes et al., 2015).

While the energy system optimization model of Chapter 2 captures numerous decisions for a complex urban energy system, it carries limiting assumptions about how technology diffusion occurs and the role of a policymaker in supporting a technology transition. Beyond well known shortcomings of this model, such as uncertain exogenous parameter assumptions, perfect foresight, and simplified temporal resolution, this model has limited power in informing optimal technology policy. First, it is unreasonable that a central planner makes all capacity investment and operating decisions for both power and transportation. Second, our optimization model essentially applies an exogenous constraint that mimics the goal of the policymaker, not the means by which she can actually achieve this policy goal. Third, our model is energy-specific and numerical: we can only cautiously apply our insights to general energy policy and the results we do obtain are highly dependent on the parameterization. And fourth, our optimization framework does not capture other drivers of adoption besides cost considerations, that arise from complex phenomena that exist in technology transitions. Indeed, while an energy system optimization model assumes that a technology transition will occur as long as a new technology becomes cost-effective, we know from empirical observations that there are a number of market failures that can hinder the diffusion of a technology even after it becomes economically competitive. The other modeling approaches, and the models in Chapters 3 and 4 try to obtain insights on these issues and policy remedies for them.

1.6.2 Stochastic models of technology adoption and diffusion

The four phenomena discussed above led to the thought that classic Markov stochastic processes were strong candidates for modeling a technology transition, with states representing stages of the diffusion process and a transition probability matrix engendering the uncertainty in success of the technology transition. Furthermore, decision making capabilities within the stochastic process could simulate policy intervention: policy intervention could map to a different transition probability matrix. The highly complex and uncertain nature of technological change implies that designing effective policy interventions is very challenging. Although pioneering works modeled technology transitions as stochastic processes, they did not incorporate technology policy decision making. In Chapter 3, we address this gap in the literature, designing a theoretical modeling framework for technology transitions featuring optimal technology policy decision making.

Modeling technology adoption and diffusion via stochastic processes is not entirely new. In the literature, we can distinguish between top-down and bottom-up stochastic models. Top-down models of technological change, like those of W. Brian Arthur, represent technology dynamics using aggregate measures like market shares of competing alternatives as the endogenous variables. Our framework goes beyond these earlier treatments by explicitly incorporating technology policy decision making under uncertainty. This allows us to obtain decision rules about optimal policy intervention rather than merely establish the properties of a stochastic diffusion process. On the other hand, bottom-up models focus on decision making under uncertainty, but the decisions being analyzed are the strategic adoption choices of individual agents in the market rather than a technology policy decision. Typically, these model the adoption and timing decisions of an individual with a choice between two competing technologies whose benefits are uncertain (Kornish, 2006; McCardle, 1985; Smith and Ulu, 2017; Ulu and Smith, 2009). While these models are well-established in the literature, they do not directly inform technology policy decision making. Adopters and policymakers face different decisions and usually have different objectives.

1.6.3 Game-theoretic models of infrastructure-dependent technology diffusion

In Chapter 4, we narrow our focus on technology transitions to infrastructure-dependent technologies common in energy, transportation, and telecommunications systems. Policymakers seeking to promote the diffusion of infrastructure-dependent technologies are often confronted with the chicken-and-egg problem: consumers are reluctant to adopt the technology without adequate infrastructure available, and firms are reluctant to invest in infrastructure without a sufficient number of adopters. This chicken-and-egg coordination problem can hinder the diffusion of new technologies and prolong the time-frame over which existing technological systems remain locked-in.

Policymakers often attempt to overcome the chicken-and-egg problem (as well as other market failures) by subsidizing both infrastructure investment and consumer purchases of the new technology. Unfortunately, the existing literature provides little guidance and few decision support tools for policymakers to determine how to optimally allocate public resources toward incentives for infrastructure investment versus consumer purchases. For example, the U.S. federal government has spent billions of dollars on tax incentives to promote the diffusion of alternative fuel vehicles and their associated refueling and charging stations. From 2009–2013, it spent 16 times as much on vehicle purchase subsidies as it did on infrastructure investment subsidies (Leibowicz, 2018a). It is difficult to assess whether that was the most beneficial use of public funds for innovation diffusion, and the existing literature offers few insights on this important public sector problem. While some previous studies have analyzed the chicken-and-egg problem and its policy implications, they tend to be either empirical studies focusing on a particular historical case study, or structural models that are constructed to examine a specific technology and omit key decision variables and interactions.

Sequential game modeling is well suited for this case, in which the policymaker subsidizes both infrastructure investment and consumer purchases of the new technology. Indeed, in reality, subsidy and adoption decisions are not simultaneous: first a policymaker sets the subsidy levels, then individuals and firms, having observed the policymaker's decisions, make their own. Furthermore, by the very nature of the chicken-and-egg problem, capturing the strategic interactions between potential adopters and the infrastructure investor is key. A number of sequential game-theoretic models in one way or another model this interaction. For example, Yu et al. (2018) use a game-theoretic framework to model the strategic interactions among three players – a policymaker, manufacturers, and consumers – where the policymaker determines both manufacturer and consumer subsidies to maximize consumer welfare subject to a policy budget constraint. However, their model does not incorporate the *infrastructure* supply for the product.

1.7 Overview

The goal of this dissertation is to advance the operations research modeling of technology transitions and the role of policy support. Through a variety of powerful operations research methodologies and relevant case studies, the individual projects in this dissertation offer novel models of technology transitions and insights into real-world technology policy.

The three projects of this dissertation employ operations research methods to model technology transitions and the role of policy support. The dissertation begins with Chapter 2, describing the development of an urban-scale energy system optimization model. This work prompted a number of research questions concerning technology transitions that motivated the more fundamental, stylized models developed in Chapter 3. Finally, the scope of this dissertation narrows with the development of a stylized model of optimal technology policy decision making for infrastructure-dependent technologies. In fact, the case studies illustrated in Chapters 3 and 4 concern the development and diffusion, respectively, of electric vehicles. This is not coincidental: designing intelligent technology policy to accelerate energy technology transitions is highly relevant today in response to climate change.

While each chapter captures a variety of phenomena affecting technology transitions and optimal technology policy decision making, there remain thought-provoking questions that future research can address. We conclude this dissertation with proposed research directions and contemplate the high-level, real-world implications of this work.

Chapter 2

Decarbonizing power and transportation at the urban scale: An analysis of the Austin, Texas Community Climate Plan

2.1 Introduction

Cities are assuming a prominent role in climate change mitigation efforts. The C40 Cities Climate Leadership Group committed to limiting global warming to 1.5°C has expanded its membership to 92 cities that encompass 25% of global GDP and 8% of global carbon dioxide equivalent (CO_2e) emissions (C40 Cities, 2018a; Center for Climate and Energy Solutions, 2018). Municipal governments from New York City (The City of New York, 2017) to London (Greater London Authority, 2016) to Tokyo (Tokyo Metropolitan Government, 2007) are implementing detailed climate action plans to reduce greenhouse gas (GHG) emissions. Given the concerns and uncertainties surrounding the future of the Paris Agreement (Rogelj et al., 2016; Tollefson, 2017), the emergence of cities as mitigation agents is an encouraging trend.

Despite the growing importance of cities in climate change mitigation, there remains a dearth of rigorous analysis to inform climate policy and mitigation strategy development at the city level (Rosenzweig et al., 2010). This

Benjamin Leibowicz contributed to the conceptualization of the topic and provided the base GAMS code, which was then extended here. A version of this chapter has been published in *Sustainable Cities and Society* (Brozynski and Leibowicz, 2018) chapter addresses this gap in the literature. We formulate an energy system optimization model in the Open Source Energy Modeling System (OSeMOSYS) framework (Howells et al., 2011) to identify cost-effective, urban-scale decarbonization pathways. It focuses on power and transportation, and captures key synergies between mitigation strategies in the two sectors. For our case study, we apply the model to evaluate the Community Climate Plan adopted by Austin, Texas in 2015. Austin is a valuable testbed for analysis because it is a member of the C40 network, has a rapidly growing population, and its Community Climate Plan established a particularly ambitious goal of net-zero GHG emissions by 2050.

The remainder of this chapter is organized as follows. The literature review in Section 2.2 covers city climate plans, energy system models, and synergies between power and transportation. Section 2.3 describes our methodology including the model and data sources. We present and discuss results in Section 2.4. Lastly, Section 2.5 concludes the chapter with a summary of its most salient findings, acknowledgment of limitations, and directions for future work.

2.2 Literature review

2.2.1 Climate policy approaches

Climate change mitigation can be viewed as a collective action problem in which individual actors make independent decisions whose outcomes jointly affect everyone (Ostrom, 2010). Climate change mitigation is a global public good; the costs are borne locally, but the benefits are distributed globally. The conventional approach to climate policy thus holds that, without an appropriate policy framework at the global scale, individual actors have insufficient incentives to curb their own emissions. The desire to establish monocentric (i.e., global) policy solutions is exemplified by international accords such as the Kyoto Protocol (Nordhaus and Boyer, 1999) and recent Paris Agreement (Schleussner et al., 2016). Progress on this scale has been slow, and the road ahead is precarious. Analysts warn that the Paris Agreement is too weak to avert dangerous climate change (Rogelj et al., 2016), and even its future is in doubt after President Trump announced his intention to withdraw the U.S. from the pact (Tollefson, 2017).

Ostrom (2010) argues in favor of an alternative, polycentric approach to climate change mitigation. Polycentric efforts involve mitigation activities undertaken by many actors at diverse scales (e.g., household, municipal, regional, national, global), as all of these actors contribute to and stand to suffer from the effects of climate change. A polycentric approach gives communities freedom to define mitigation strategies that best suit local conditions, encourage broad participation, and generate desired co-benefits (e.g., improve air quality, enhance energy access, increase employment). The cumulative effect of polycentric efforts can be significant at the global scale.

2.2.2 City climate plans

In line with the polycentric approach, many cities around the world have enacted plans to curb GHG emissions at the urban scale. Notable examples include the London Plan (Chapter 5) to reduce emissions to 60% below 1990 levels by 2025 (Greater London Authority, 2016), New York City's commitment to limit global warming to 1.5°C in alignment with the Paris Agreement (The City of New York, 2017), and the Austin Community Climate Plan to achieve net-zero GHG emissions by 2050 (City of Austin, 2015). The Austin plan is particularly ambitious, and serves as our case study application for the model we develop.

Creating an effective city climate plan requires a detailed understanding of the urban energy system, including an accurate inventory of GHG emissions. Without a reliable inventory, it is difficult for city planners to identify where efforts should be directed (Grubler et al., 2012). Ramaswami et al. (2011) outline several methods of accounting for urban GHG emissions. A "purely geographic production-based" scheme is likely misleading for cities with large electricity imports and commuting across municipal boundaries. Furthermore, how a city's boundaries are defined may lead to dramatically different GHG emissions inventories. A more appropriate accounting scheme for cities might be a "geographic-plus infrastructure supply chain" method that accounts for emissions which occur upstream in key trans-boundary infrastructures that serve the city (e.g., electric grid, road transportation network). A third alternative is "pure consumption-based" accounting that attributes the full GHG footprints of all goods and services consumed by local households and firms to the city inventory. For reference, total consumption-based emissions of 79 C40 cities are 60% greater than production-based emissions, indicating that cities affect emissions far beyond their physical boundaries (C40 Cities, 2018b). Whether a production-based or consumption-based accounting scheme is preferable when considering a city's response to climate change is not imme-

See Stone et al. (2012) for a review of climate plans from the 50 most populous municipalities in the U.S.

For example, C40 membership applies only to the jurisdictional boundary of the participating city authority. As an extreme contrast, Melbourne's jurisdiction is only the central business district, with an area of 6.2 km^2, whereas London's jurisdiction encompasses all of Greater London, with an area of 1579 km^2.

diately clear. On the one hand, production-based accounting aligns with GHG emissions sources over which the city has the most direct influence. On the other hand, consumption-based accounting incentivizes planners to foster more sustainable consumption patterns and urban lifestyles. Hillman and Ramaswami (2010) present GHG inventories for eight major U.S. cities, including Austin.

2.2.3 Austin Community Climate Plan

Austin is a rapidly growing city with approximately 948,000 inhabitants in 2016, a sharp increase from 790,000 in 2010 (U.S. Census Bureau, 2016). The City of Austin is at the center of a metropolitan statistical area (MSA) that is home to roughly 2,056,000 people and growing at more than four times the rate of the U.S. population as a whole. The MSA is projected to have a population over 5 million by 2050 (Austin Chamber of Commerce, 2018). Despite its demonstrated commitment to sustainability (described below), Austin has relatively high per-capita GHG emissions compared to other U.S. cities (Glaeser and Kahn, 2010). Contributing factors include: a humid subtropical climate that induces strong air conditioning demand; a sizable (but rapidly declining) coal share of electricity generation; a dispersed settlement pattern dominated by single-family, detached houses; and a transportation sector heavily dependent on private automobile use. For addressing emissions, the Austin municipal government has the unique advantage of controlling its electric utility, Austin Energy. In fact, it is the eighth largest publicly owned electric utility in the U.S. (Austin Energy, 2018).

Austin has a strong tradition of promoting sustainability and combatting climate change. In 2007, the Austin City Council passed a resolution to "make

Austin the leading city in the nation in the effort to reduce the negative impacts of global warming" (City of Austin, 2007). Since then, the City Council has adopted targets to reduce emissions and transition to renewable energy. In 2010, the City Council approved the Austin Energy Resource, Generation, and Climate Protection Plan to 2020 (Austin Energy, 2010), with a goal of meeting 35% of all energy needs with renewable resources by 2020. This renewable share is to feature at least 200 MW of solar power, of which 50% is local solar and 25% is specifically customer-owned solar. Austin has already achieved some ambitious goals. For example, all municipal buildings now operate exclusively on renewable energy.

In 2014, the City Council passed a resolution officially establishing "a goal of reaching net zero greenhouse gas emissions by 2050" (City of Austin, 2014). One year later, the Office of Sustainability produced the Austin Community Climate Plan (ACCP) (City of Austin, 2015) to formalize and delineate this vision. The ACCP aims to set Austin on a path of economic and environmental sustainability, establish Austin as a global leader in addressing climate change, and provide an example policy framework for other cities to follow. Figure 2.1 illustrates the GHG emissions path that the ACCP establishes through 2050, including interim targets to be reached along the way. Indeed, Austin plans to exceed the 80% (relative to 2005 levels) reduction in GHG emissions by 2050 which had been targeted by the Obama administration and incorporated into its Intended Nationally Determined Contribution to the Paris Agreement. The plan document acknowledges that Austin is already experiencing climate change impacts including more frequent wildfires and flooding, persistent drought conditions, violent precipitation, recording-breaking summer temperatures, more days above 110°F, and more nights

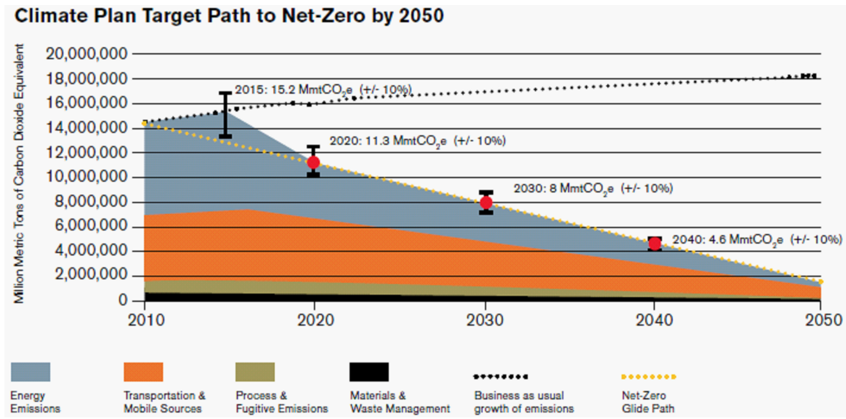

Figure 2.1. GHG emissions path through 2050 established in the Austin Community Climate Plan (City of Austin, 2015).

above 80°F. It projects that these phenomena will increase in frequency and magnitude over time. At the city scale, these changes could inflict heavy economic, social, and environmental costs.

To develop the ACCP, the Office of Sustainability began by ordering a full GHG inventory for Travis County. This effort followed the recommendations of the U.S. Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions (ICLEI, 2012) and measured emissions in the following categories: 1) use of electricity, 2) use of fuel in residential and commercial air and water heating, 3) passenger and freight travel, 4) landfills, and 5) industrial processes. Some emissions sources, however, were excluded: emissions from the extraction of raw materials, the manufacture and transportation of foods and goods to Austin, upstream emissions from the extraction and processing of fossil fuels, air travel, and natural carbon capture (offsetting emissions). This inventory methodology most closely aligns with the purely geographic production-based accounting scheme. Based on findings from King County, Washington, consumption-based accounting could lead to total emissions that

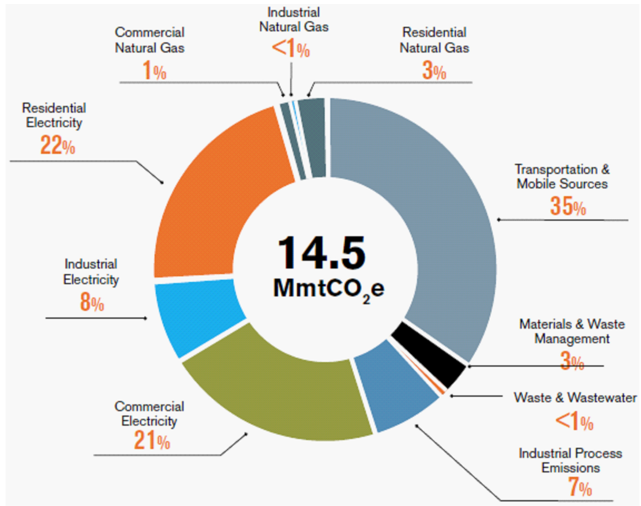

Figure 2.2. Austin GHG inventory for 2010 (City of Austin, 2015).

are 160% higher (City of Austin, 2015). The GHG inventory results shown in Figure 2.2 reveal a few high-level characteristics of Austin's energy system. First, the use of natural gas as a heating fuel is quite limited in Austin, but electricity generation accounts for over half of all GHG emissions. Second, transportation accounts for 35% of emissions, 94% of which are due to on-road cars and trucks. Third, industrial emissions make up a fairly small share of the total, and are mainly associated with lime production and semiconductor manufacturing. So, the obvious sectors to target for reducing emissions are power and transportation, which combine to produce 86% of Austin's emissions.

The Office of Sustainability convened four technical advisory groups (electricity and natural gas, transportation, waste management, and industrial

Austin is heavily dependent on private automobile use for transportation and is plagued by traffic congestion. In 2016, the average Austinite spent 47 hours in traffic, making Austin the 13th most congested city in the country.

processes) to define strategies for cost-effectively reducing emissions. The ACCP includes a detailed outline of specific mitigation actions that can be implemented in each sector. Identified actions include improving building energy efficiencies, investing in energy storage technologies and smart grid systems, shifting power generation to renewable energy, and demand-side management. In 2016, the Office of Sustainability released an Implementation Plan for Phase I of the ACCP (City of Austin, 2016), the period leading up to the 2020 interim target. It highlights 58 actions from the ACCP that are expected to contribute to meeting the 2020 target. Austin appears on track to achieve its near-term goal, primarily because Austin Energy has swiftly increased the share of renewables in its electricity generation portfolio.

Finally, the ACCP establishes a rigorous reporting cycle, with frequent revisions, progress reports, and GHG inventories to keep Austin on track to achieve its net-zero goal. In addition to its core environmental purpose, it is hoped that the ACCP will help ensure access to affordable energy and alleviate Austin's congested transportation networks.

2.2.4 Energy system optimization models

Pfenninger et al. (2014) distinguish four energy system modeling paradigms: 1) energy system optimization models, 2) energy system simulation models, 3) power systems and electricity market models, and 4) qualitative and mixed-method scenarios. The framework we develop herein belongs to the first of these classes.

Energy system optimization models contain detailed, bottom-up representations of the technological components that constitute an energy system. They are used to explore how energy systems are likely to evolve – or should ideally evolve – over some specified timeframe, depending on techno-economic assumptions and policy settings. An evolution of the energy system is known as a transformation pathway, defined by the collection of all technology investments and operational decisions. Energy system optimization models are typically constructed to identify the least-cost transformation pathway that satisfies all energy demands as well as a host of other constraints. By introducing additional parameters or constraints, energy system optimization models can be used to analyze a range of energy and climate policies. Specific questions that they intend to answer include: 1) Is it possible to achieve an emissions target given available technologies and constraints on their deployment? 2) What is the economic cost of achieving a climate policy goal? 3) What technological transformation pathway allows a policy goal to be accomplished most cost-effectively? Well-known optimization frameworks include the MARKAL/TIMES family (Loulou et al., 2004; Loulou and Labriet, 2007; Loulou, 2007), MESSAGE (Messner and Strubegger, 1995; Messner and Schrattenholzer, 2000), and OSeMOSYS (Howells et al., 2011).

Despite the growing importance of city mitigation efforts, energy system optimization models are typically applied at the national or global scale. In fact, there are very few examples in the literature describing urban-scale application of these frameworks. Lin et al. (2010) employ the LEAP model to study GHG emissions reduction in Xiamen, China. Their model incorporates a variety of mitigation strategies including clean energy substitution (natural gas largely replaces coal and diesel in industry and transportation), renewable energy development, and motor vehicle control. They find that clean energy substitution is the most effective measure. Comodi et al. (2012) use the TIMES model to analyze the effects of several climate policies in Pesaro, Italy, a small seaside municipality. The authors find that carbon policies promoting the diffusion of solar technologies reduce energy consumption, but are costly for residents. Ma et al. (2015) apply the MARKAL model to Shanghai, China, a city plagued by intense coal use. Under a climate policy, coal is gradually replaced by natural gas, which reduces emissions. They do not, however, consider transportation. Rosenzweig et al. (2010) argue that far more research is needed on urban-scale mitigation in order to guide city governments toward effective policy solutions. The chapter addresses this gap in the literature, advancing the application of energy modeling at the city level, and using this approach to evaluate an enacted city climate plan rather than a set of hypothetical policy scenarios.

2.2.5 Synergies between power and transportation

The power and transportation sectors are the two largest GHG emitters in the U.S., accounting for 28% and 29% of total emissions, respectively (EPA, 2017b). Evidence suggests that these shares are even higher in urban areas, and in Austin these two sectors account for 86% of emissions (see Figure 2.2). Any serious effort to decarbonize cities will therefore require monumental changes in how we generate electricity and travel from place to place. At present, transportation and power are largely decoupled, at least in the U.S. Petroleum products dominate the fuel mix of the former, but have been almost completely phased out of the latter. This situation is likely to change in the future as transportation shifts to alternative fuels that are more closely linked to the power sector, especially under climate policies (Anandarajah et al., 2013; Bosetti and Longden, 2013; Edelenbosch et al., 2017; Pietzcker et al., 2014). Amid this trend, powerful synergies will emerge whereby mitigation activities in power and transportation mutually enhance one another. We design our model to leverage these synergies while optimizing decarbonization pathways.

Use of electricity as a transportation fuel causes larger marginal GHG emissions reductions as the power sector decarbonizes upstream. This is one reason why most energy-economy models choose to decarbonize electricity generation before investing significantly to convert transportation fleets to electric vehicles (Löffler et al., 2017; Pietzcker et al., 2014). Electrification of transportation would increase overall demand levels in the power sector, necessitating greater capacity utilization and/or additional capacity investments. Hydrogen fuel cell vehicles can also provide carbon-free transportation if hydrogen is produced via electrolysis using renewable electricity (Anandarajah et al., 2013). So, the hydrogen route to sustainable mobility is also enhanced by decarbonizing the power sector.

In the reverse direction, uptake of alternative fuel vehicles facilitates the integration of intermittent renewables into the power sector and provides valuable services to the electric grid. Electric vehicle charging can be managed as a flexible load to absorb renewable electricity during periods of excess supply. Choi et al. (2013) demonstrate that intelligently scheduling electric vehicle charging reduces the cost of complying with a renewable electricity standard in the power sector. Hydrogen production via electrolysis can similarly be considered a flexible load, occurring when renewable energy is abundant to provide fuel for hydrogen-based vehicles. In a vehicle-to-grid (V2G) system, electric vehicle batteries are capable of supplying power to the grid at times of peak demand or low renewable resource availability. With widespread adoption of electric vehicles, V2G could encourage further deployment of renewable technologies and reduce investments in peaking power plants or stand-alone energy storage technologies (Nunes et al., 2015).

2.3 Methodology

2.3.1 Standard OSeMOSYS

OSeMOSYS is a highly flexible and modular energy system optimization framework that can be applied to problems ranging in scope from an electricity microgrid to a comprehensive global energy system (Howells et al., 2011). It has much in common with other bottom-up, technologically detailed energy models such as MARKAL/TIMES (Loulou et al., 2004; Loulou and Labriet, 2007; Loulou, 2007) and MESSAGE (Messner and Schrattenholzer, 2000; Messner and Strubegger, 1995). However, unlike these other models, the standard OSeMOSYS source code is publicly and freely accessible, and thus addresses a gap in the existing toolbox while enhancing energy modeling research transparency. The standard version of OSeMOSYS can be run via a user-friendly, web-based interface. Nevertheless, research teams have developed customized OSeMOSYS implementations in a variety of programming environments to tailor the framework to specific problems. OSeMOSYS applications appearing in the literature include high renewable penetration in Ireland (Welsch et al., 2014), electric capacity planning under policy uncertainty (Leibowicz, 2018b), climate resilience of African infrastructure (Cervigni et al., 2015), and competing objectives in the Saudi Arabian power sector (Groissböck and Pickl, 2016).

OSeMOSYS is formulated as a linear program that determines the least-cost technology capacity additions and operational schedules that satisfy exoge-

Please see www.osemosys.org for the most up-to-date information about OSeMOSYS.

nous demands, subject to a host of constraints. The model consists of a collection of component blocks, each of which can be described at four different levels of abstraction: 1) a plain English description, 2) an algebraic formulation of the plain English description, 3) an implementation of the algebraic formulation in a particular programming language, and 4) a parameterization corresponding to the specific energy system being modeled. For example, consider the "Energy Balance" component block. In plain English, "Energy Balance" ensures that in each year, timeslice, and region, production of each fuel is sufficient to satisfy final demand for that fuel plus use of that fuel as an intermediate input to other processes. An algebraic formulation of the essential equation within the "Energy Balance" block is given in Eq. (2.1). In this study, the third level of abstraction is our implementation of this equation in the General Algebraic Modeling System (GAMS) source code we develop for OSeMOSYS. The fourth level of abstraction is achieved by parameterizing this equation using data for our Austin application. A similar breakdown could be provided for the objective function in Eq. (2.2), which computes the net present cost of the energy system. Other component blocks model storage, operating constraints, and emissions accounting.

Energy system optimization models typically divide each year into a computationally tractable number of representative timeslices. These timeslices allow a model to capture temporal variability of parameters such as demands and intermittent renewable resource capacity factors. They also allow a model to solve for simplified operational schedules (i.e., dispatch).

In Eqs. (2.1) and (2.2), Y is the set of years, L is the set of timeslices, F is the set of fuels, R is the set of regions, and T is the set of technologies. Corresponding lower-case letters refer to elements of these sets.

$$\forall y \in Y, l \in L, f \in F, r \in R, \quad \text{Production}_{y,l,f,r} \geq \text{Demand}_{y,l,f,r} + \text{Use}_{y,l,f,r} \tag{2.1}$$

$$\begin{aligned} \text{minimize} \sum_{y,t,r} [&\text{DiscountedOperatingCost}_{y,t,r} + \text{DiscountedCapitalInvestment}_{y,t,r} \\ &+ \text{DiscountedTechnologyEmissionsPenalty}_{y,t,r} - \text{DiscountedSalvageValue}_{y,t,r}] \\ &+ \sum_{y,r} \text{DiscountedDemandResponseCost} \end{aligned} \tag{2.2}$$

An OSeMOSYS database for a particular application defines “fuels” and “technologies,” terms which have expansive interpretations in the context of the model. A “fuel” is any energy commodity, energy carrier, or energy service that is a process input, process output, or demanded by consumers. The set of fuels can thus include coal, gasoline, electricity, hydrogen, vehicle miles traveled (VMT), and so on. A “technology” is any device that converts input fuels into output fuels. Example technologies that can be defined include coal power plants that convert coal into electricity, steam methane reforming that converts natural gas into hydrogen, and internal combustion engine vehicles that convert gasoline into VMT. Technologies do not necessarily need to have an input fuel. In modeling an electric utility, for instance, coal is purchased rather than produced within the model. So, purchasing coal can be represented as a technology that consumes no input, produces coal as an output, and has only variable cost (i.e., the exogenously specified coal price). Renewable resource potentials are represented in much the same manner, except all costs are zero and quantity constraints are imposed to reflect natural limits on available resources. Certain fuels are associated with many different technologies and demands throughout a database. Electricity can be generated using many combinations of feedstock and power plant, is demanded by consumers, and is an intermediate input to technologies such as hydrogen electrolysis, electric vehicles, and battery electricity storage (for which electricity is also the output). Each technology in the database is represented by exogenously specified parameter values for costs (capital, fixed O&M, variable O&M), capacity factors, residual capacities, efficiencies, lifetimes, capacity and operating limits, GHG emission rates, and so on.

2.3.2 Model implementation and customization

For this study, we modify the standard OSeMOSYS framework to determine optimal energy system transformation pathways for achieving decarbonization goals at the urban scale. We implement our version of OSeMOSYS in the GAMS language and solve it using CPLEX. Our GAMS code is based on an earlier translation of OSeMOSYS into GAMS by Noble (2012), and extends the code developed by Leibowicz (2018b). We build a database for Austin and apply OSeMOSYS to evaluate the ACCP. To ensure that our framework covers the vast majority of GHG emissions in Austin, we fully integrate a transportation sector into the model. This integration requires several modifications to the standard, power-centric OSeMOSYS framework.

First, we add constraints to make private transportation non-dispatchable. While an electric utility can centrally decide how to optimally operate its generator fleet during every hour of the day, the private vehicle fleet cannot be optimally coordinated. That is, if there is a mix of different vehicle types in the fleet, there is no reason to believe that they could be dispatched in ascending order of variable cost in order to satisfy the private transportation demand in a given hour. We handle this distinction by requiring that the production of private vehicle miles by each vehicle type in any timeslice be proportional to its share of the overall vehicle fleet. For example, if electric vehicles comprise 10% of the private vehicle fleet, then 10% of the private vehicle miles produced in any timeslice must come from electric vehicles. This constraint would ordinarily make the model nonlinear, as the fleet size and operational variables are both enodgenously determined within the model. To preserve linearity, we exogenously calculate the fleet size needed to satisfy the peak private transportation demand assuming an average travel speed and capacity factor for all vehicles. In addition, we constrain the number of miles a vehicle can travel in a given year; the average American drives less than 15,000 miles annually (DOT, 2017).

Second, unlike conventional fossil fuel transportation technologies, electric vehicles introduce the need to model not only their driving activity, but also their charging activity. In addition, V2G capability, whereby electric vehicle batteries can discharge back to the grid, must be modeled in a way that balances charging, discharging, and driving activity. Indeed, vehicles that are out driving can neither charge nor provide V2G power. Because electricity dispatch is determined endogenously, it is also important to coordinate electric vehicle charging as a flexible load. For example, electric vehicles might be charged during hours of high renewable power output or low electricity

For example, assuming all vehicles operate at an average speed of 30 mph and 3 million miles are demanded everyday from 5–6 PM (peak rush hour), then 100,000 vehicles need to be operating in this hour to satisfy demand. However, only 20% of the available vehicle fleet is on the road at any time, so the size of the total vehicle fleet should be approximately 500,000.

demand. Allowing the model to optimize charging schedules may constitute an important synergy between power and transportation that could facilitate the integration of renewables into the electricity mix (Choi et al., 2013). Our formulation includes an electric vehicle battery technology, essentially an aggregation of all electric vehicles, similar in spirit to the formulation of Zakeri and Syri (2015). The battery technology charges at a rate consistent with the aggregate power rating, and the electricity stored is used to power electric vehicles while driving or provide V2G power while idle. Timeslice-dependent capacity factors ensure that only idle vehicles can charge. For example, if 10% of electric vehicles are out driving in a given hour, then the aggregate electric vehicle battery technology can charge at up to 90% of its maximum rate (that is, 90% of electric vehicles are plugged in and available to charge). For V2G discharging, we further reduce these capacity factors to reflect EV owners' limited willingness to make their vehicles available for V2G at various times. We parameterize nighttime and daytime V2G capacity factors to be 75% and 25%, respectively, of those for charging the battery. For example, if 90% of electric vehicles are idle during a nighttime hour, then 75% of these will be made available for V2G for a resulting capacity factor of $0.9 * 0.75 = 67.5\%$. If 90% of electric vehicles are idle during a daytime hour, then only 25% of these will be made available for V2G (presumably because their owners want to keep their batteries charged up in case they need to drive) for a lower capacity factor of $0.9 * 0.25 = 22.5\%$. Enabling electric vehicles for V2G comes at the capital cost of the power inverter installed at home or in the workplace, parameterized at 1.5 times the cost of power inverters for utility-scale lithium-ion batteries (Zakeri and Syri, 2015). Our formulation thus allows the model to optimally schedule electric vehicle charging and V2G discharging, and ensures that these activities, along with driving, are mutually exclusive for a vehicle in a given hour.

Third, we add capacity growth constraints to prevent individual technologies from scaling up at unreasonably rapid rates as economic and policy parameters evolve. Without these constraints, optimization-based energy models are likely to yield "bang-bang solutions" where the capacity mix changes radically from one period to another due to a slight change in the relative costs of technology options. Capacity growth constraints are commonly imposed in energy system models (Iyer et al., 2015; Wilkerson et al., 2015), but are absent from the standard version of OSeMOSYS. We include them in our implementation to place some realistic limits on feasible energy system transformation pathways. Specifically, we constrain the new capacity addition in the current period to be less than some fraction of the previous period's total installed capacity, plus a start-up value that enables initial capacity investment in new technologies with no existing capacity.

Fourth, we ensure that the energy system is capable of satisfying demands even under extreme conditions that are not captured by the representative timeslices. Reducing all variability throughout the year to hourly profiles for representative seasonal days necessarily entails aggregation. For example, the representative timeslices should capture the fact that electricity demand is higher in summer than in winter for a system with strong air conditioning load, but the peak demand hour occurring on the hottest summer day would be averaged away in determining the representative summer profile. Alternatively, by averaging hourly wind capacity factors over a season, the representative profile would not account for certain hours when wind generation is zero. This extreme would be problematic for a system heavily reliant on wind turbines. To address these extremes, we add two constraints to ensure that there is adequate capacity to meet demand during the peak load hour of the year, as well as an hour with zero wind generation and high load. These constraints can be satisfied by dispatchable generators, renewable installations operating at their hour-specific capacity factors, demand response, and one quarter of total storage capacity. The model incurs the cost of any additional capacity required to cope with these extreme hours, but they are not explicitly incorporated into the dispatch computation based on representative seasonal days. This is consistent with the notion that demand peaks drive capacity investments while typical conditions drive operating costs.

Fifth, we add demand response capability to the model. The ability to strategically pay customers to reduce load during high-net-load hours will be increasingly important as the power sector shifts further toward renewables. Leveraging demand response allows a utility to save on operating cost by avoiding the use of high-variable-cost peaking plants, and on capital cost by avoiding additional investments that would otherwise be needed to meet peak load plus reserve margin. In our implementation, the optimization routine chooses the amount of demand response to deploy, and these variables get subtracted from the exogenous hourly demand for a fuel in a given timeslice. Demand response has a stepped supply curve, so that limited amounts of demand response are available at three specified cost levels (low, medium, and high).

Sixth, we integrate purchases of carbon offsets into the model. There is some ambiguity in the ACCP in that Austin emissions are not required to decline all the way to zero, but to some near-zero level with the difference made up by purchasing offsets. Our interpretation is that actual Austin emissions must decline by at least 90% by 2050, and that offset purchases can account for the remainder (up to 10%). By adding an OSeMOSYS technology whose operation reduces the annual emissions level at a variable cost equal to the price of carbon offsets, we allow the model to endogenously choose whether to achieve the last 10% of emissions reductions that the ACCP mandates by directly eliminating those emissions or by purchasing offsets. The 10% maximum is imposed as a constraint on the operations of the offset purchasing technology.

2.3.3 Austin database

We consider the evolution of Austin's power and transportation sectors in annual time steps from 2015–2050. The database includes 72 representative timeslices for each year, corresponding to hourly profiles for representative summer, winter, and spring/fall days. The use of 24-hour profiles is important for faithfully representing intra-day variability in demands and renewable capacity factors, and for modeling the operation of storage technologies. From our perspective, this use of timeslices is a major improvement compared to typical approaches that divide days into far fewer timeslices, such as crude daytime and nighttime divisions (Lenox et al., 2013). Our hourly profiles are essential for capturing synergies between the power and transportation sectors, such as flexible electric vehicle charging and V2G storage.

While the ACCP was executed by the Austin City Council, whose jurisdiction is the City of Austin, the GHG emissions inventory ordered is for all of Travis County, of which the City of Austin makes up 81% of the population. Additionally, 97% of Austin Energy's service area is within the boundaries of Travis County (see Figure 2.3). Whereas most fossil fuel and solar PV generation occurs in and around Austin, most wind electricity is imported

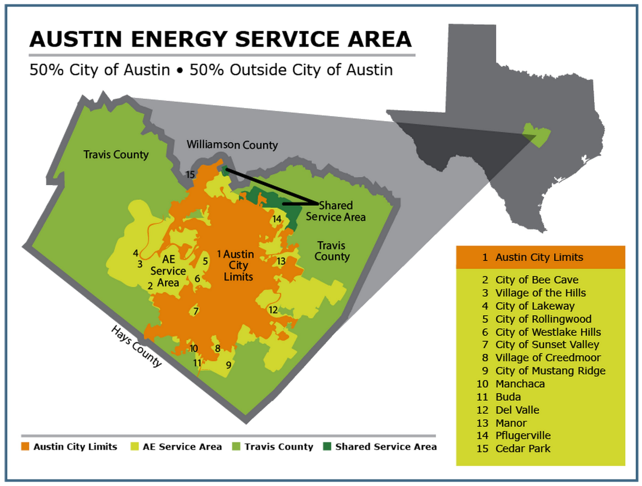

Figure 2.3. Austin Energy Service Map of 2015 (Austin Energy, 2018).

from West and South Texas. Furthermore, Texas transportation data are only available by county, allowing us to capture most commuting activity. Therefore, considering the data collection boundaries and Austin Energy's service area, we take Travis County as the geographical scope of our analysis.

Table 2.1 lists the technologies included in our Austin database for OSeMOSYS. Transportation technologies are split into two categories: private transportation and public transportation. Furthermore, we use two separate "fuels" to represent private and public transportation demands: VMT and passenger miles (PM), respectively. These demands cannot substitute for one another; that is, no portion of private transportation demand can be met by public transportation vehicles, and vice versa. While substitution could occur in the long run, transportation demand in Austin is not expected to shift significantly towards public options due to persistent infrastructural, behavioral, and settlement pattern lock-in effects (Seto et al., 2016).

The database includes three final demand categories: electricity, VMT

Table 2.1. Technologies in the OSeMOSYS Austin database.

Power Plants	Coal-fired	*COAL*
	Gas-fired combined cycle	*GAS CC*
	Gas-fired combustion turbine	*GAS CT*
	Nuclear	*NUCLEAR*
	Hydroelectric	*HYDRO*
	Wind turbine	*WIND*
	Solar photovoltaic	*SOLAR*
	Biomass	*BIOMASS*
	Gas-fired combined cycle with carbon capture and storage	*GAS CC CCS*
	Integrated coal gasification combined cycle with carbon capture and storage	*IGCC CCS*
	Hydrogen fuel cell	*H2 FUEL CELL*
Private Vehicles	Gasoline-powered internal combustion	*GASOLINE*
	Diesel-powered internal combustion	*DIESEL*
	Plug-in gasoline-electric hybrid	*PHEV*
	Gasoline-electric hybrid	*HYBRID*
	Hydrogen fuel cell	*H2*
	Electric	*EV*
Public Vehicles	Gasoline-powered internal combustion	*GASOLINE*
	Diesel-powered internal combustion	*DIESEL*
	Compressed natural gas-powered internal combustion	*CNG*
	Biodiesel-powered internal combustion	*BIODIESEL*
	Plug-in gasoline-electric hybrid	*PHEV*
	Gasoline-electric hybrid	*HYBRID*
	Electric	*EV*
Hydrogen Production	Electrolysis	*ELECTROL*
	Natural gas steam reforming	*GASREF*
	Biomass gasification	*BIOGAS*
	Coal gasification	*COALGAS*
Storage	Battery	*BATTERY*
	Electric vehicle battery[a]	*EV BATTERY*

[a] The EV BATTERY technology powers electric vehicles during use and can provide V2G power.

(private transportation), and PM (public transportation). Our database is unique in that it represents both electricity and transportation demands at hourly resolution for representative seasonal days. Even other models that

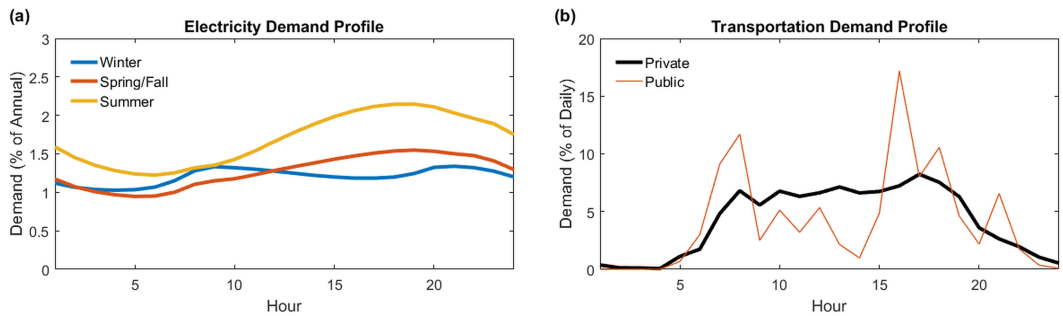

Figure 2.4. Demand profiles from the Austin, Texas database that are inputs to the model. The vertical axes measure the percentage of total annual demand occurring in each timeslice. Transportation demand profiles are the same in all seasons, while electricity demand profiles are season-specific. Since spring and fall seasons are combined, the total demand over the two seasons is actually double the orange line values in Figure 2.4a, which are averages for the two seasons.

represent electricity using 24-hour profiles tend to include transportation as a non-time-specific demand. Table 2.2 provides detailed documentation of data sources for our input parameter value assumptions.

Figure 2.4 illustrates the representative demand profiles that are inputs to the model. Figure 2.4a shows the average electricity demand profile in each season. Electricity demand is significantly higher in summer due to Austin's humid subtropical climate that induces strong air conditioning load, which peaks in early evening. Heating loads tend to be limited, but because Austin residents predominantly use electric rather than natural gas heating, the winter demand profile has noticeable peaks in the morning and evening. Figure 2.4b displays transportation demand profiles for VMT and PM. Note that seasons are not considered, as we have no strong reason to believe transportation demands vary greatly across seasons. Both VMT and PM fall to nearly zero during the night. VMT demand is relatively constant during daylight hours,

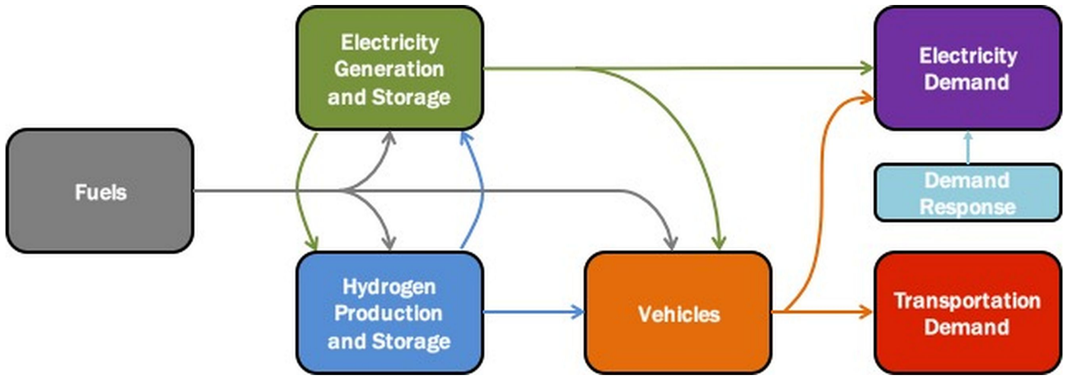

Figure 2.5. Visual overview of the OSeMOSYS database constructed for Austin. The diagram highlights synergies among electricity, hydrogen, and transportation.

but exhibits small peaks during the morning and evening rush hours. PM demand is far more concentrated within the rush hours, because a majority of passengers only use public transportation to commute to and from the workplace. Future transportation and electricity demands are taken to be exogenous, and are established based on projections of Austin's population growth (Austin Chamber of Commerce, 2018).

Figure 2.5 provides a visual overview of the OSeMOSYS database constructed for Austin. For clarity, it does not represent individual technologies and fuels, as there are simply too many of these in the database to incorporate into an overview diagram. Instead, Figure 2.5 depicts the exchanges that take place between different sectors in the model. For example, the hydrogen production and storage sector includes technologies that consume fossil fuels (gray input arrow) and electricity (green input arrow). The hydrogen they produce (blue output arrows) is demanded by hydrogen fuel cells in the electricity generation and storage sector and by hydrogen fuel cell vehicles in the vehicles sector. In addition, demand response may directly lower electricity demand (light blue arrow). Figure 2.5 highlights the numerous synergies among electricity, hydrogen, and transportation that system optimization can exploit to identify a universal solution that is superior to the combination of solutions that would be individually optimal for each sector in isolation.

Table 2.2. Documentation of data sources for input parameter value assumptions.

Parameter	**Source**
Annual electricity demand	ERCOT (2017b)
Annual electricity demand projections	ERCOT (2015)
Fraction of annual electricity demand in each timeslice	ERCOT (2015)
Annual private transportation demand	TXDOT (2016)
Annual private transportation demand projections	FHWA (2017)
Annual public transportation demand	DOT (2015)
Fraction of transportation demand in each timeslice	DOT (2015)
Average wind capacity factor by timeslice	ERCOT (2017a)
Average solar capacity factor by timeslice	NREL (2016)
Base year power plant capacity mix	Austin Energy (2017)
Base year private transportation fleet mix	TXDMV (2017)
Base year public transportation fleet mix	CapMetro (2016)
Power plant conversion efficiencies	EIA (2017)
Vehicle efficiencies	EIA (2017)
Power plant and fuel cost projections (investment, fixed O&M, variable O&M)	NREL (2017)
Vehicle capital and variable costs, costs for chargers and installation	EIA (2017), Home Advisor (2018)
Power plant CO_2 emission rates	Schlomer et al. (2014)
Vehicle CO_2 emission rates	EPA (2017a)
Battery electricity storage cost assumptions	Zakeri and Syri (2015)
Demand response availability and costs	SPEER (2015)
Hydrogen production costs	Thengane et al. (2014)

2.3.4 Policy scenarios

To evaluate the ACCP, we compare a Climate Plan scenario to a Baseline scenario. In particular, we seek to quantify the economic cost of the ACCP, and to assess how the technology mixes of the power and transportation sectors should evolve over time to achieve its decarbonization goal most cost-effectively.

The Baseline scenario is a business-as-usual development of the power and transportation sectors in which investment and operational decisions are optimized in the absence of a carbon policy. The Climate Plan is represented by imposing an exogenous upper limit on emissions in each year, consistent with the linear decline path depicted in Figure 2.1. Based on our interpretation, we assume in our Climate Plan scenario that total annual CO_2 emissions must be reduced to zero by 2050, with carbon offsets at most 10% of the difference between 2015 emissions and the exogenous upper limit in each year.

In addition to the Climate Plan scenario with a 10% carbon offset allowance, we also run the model for gradually more stringent variations where the carbon offset allowance is reduced to 8%, 6%, 4%, 2%, and 0%. While we do not report all these results in great detail due to space constraints, it is instructive to see how the policy cost increases as the allowed contribution of carbon offsets is restricted. Furthermore, we conduct some sensitivity analysis on the price of carbon offsets. Eliminating the last few percent of emissions could be very expensive on the margin if offsets are unavailable or their price is high.

2.3.5 Additional scenarios

In addition to the main Baseline and Climate Plan scenarios, we consider Public Transportation variants featuring significant mode shifting from private to public transportation. Specifically, VMT are gradually converted into PM over the model timeframe so that 50% of VMT from the main scenarios in 2050 is shifted to PM. In converting VMT into PM, we assume that a public bus has an average occupancy of ten passengers. Indeed, the ACCP advocates shifting transportation demand from private to public modes as an important climate change mitigation lever (City of Austin, 2015). The Public Transportation scenarios thus help us assess the potential benefits of such a transition.

Finally, we also consider Charging Cost variants of our main scenarios in which the cost of electric vehicle battery chargers and their associated installation costs are included in the capital costs of electric vehicles, both private and public. Therefore, the Charging Cost case effectively makes electrified transportation more expensive.

2.4 Results and discussion

2.4.1 Policy cost

OSeMOSYS determines the least-cost transformation pathway for the integrated power and transportation system. The objective value associated with the optimal pathway thus represents the net present cost of satisfying the city's power and transportation demands over the period 2015–2050. By comparing the objective values in the Baseline and Climate Plan scenarios, we can quantify the cost of the policy.

The Baseline scenario results in a net present cost of approximately $89.0 billion. The corresponding value in the Climate Plan scenario (10% carbon offset allowance) is $91.4 billion. The Climate Plan restricts the feasible set

We assume a relatively standard 5% discount rate.

of solutions that the model has to choose from, so it is unsurprising that the policy increases costs. In relative terms, the ACCP raises net present power and transportation costs by about 2.7%. This economic impact is not trivial, but in our view, 2.7% is a relatively modest cost given the stringency of the ACCP. This result demonstrates that power and transportation can be deeply decarbonized at the urban scale without incurring exorbitant mitigation costs. It also reflects significant cost reductions in clean energy technologies over recent years which have made increasingly ambitious emissions targets economically acceptable.

Ultimately, the policy cost will be borne by residents through some combination of higher electricity rates, the need to purchase vehicles with lower emissions, higher public transportation fares, and additional taxes. Mitigation strategies in the power sector and public transportation can be directly implemented by the city, which controls its electric utility and manages the bus fleet. Getting residents to purchase less emissions-intensive vehicles would require complementary policies such as financial incentives, infrastructure deployment programs, or mandates. Our analysis reveals how the net-zero GHG emissions goal can be achieved most cost-effectively in terms of the system-wide decarbonization pathway, but does not delve into the specific regulations required to induce all components of that pathway.

Figure 2.6 illustrates the sensitivity of net present cost to the carbon offset allowance. Reducing the allowance from 10% down toward 0% increases the stringency of the policy by forcing the system to directly eliminate its last remaining emissions. Of course, reducing the offset allowance makes the policy more expensive. Requiring the power and transportation sectors to be totally carbon-free results in a net present cost of $92.0 billion, roughly $0.6 billion

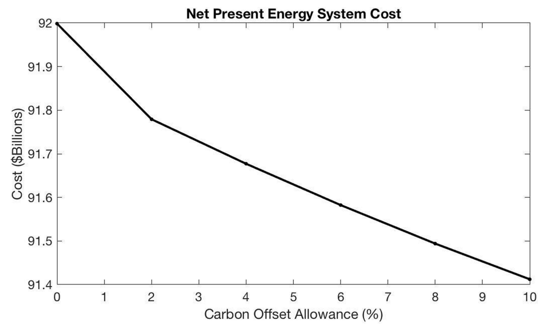

Figure 2.6. Sensitivity of the net present cost objective value to the carbon offset allowance.

more than that with the 10% allowance. The relationship between cost and offset allowance is roughly linear except for the difference between the 2% and 0% allowances. The last 2% of emissions are marginally more expensive to eliminate because they necessitate a lot of additional storage capacity and even force public transportation (the most expensive demand to decarbonize) to fully electrify.

We performed some experiments by raising the carbon offset price from its reference value of $20/t$CO_2$. Interestingly, the offset price has to be many times higher than this for the model to choose to make less than full use of the offset allowance. The constraint on offset purchases remains binding until the price nears $150/t$CO_2$, and some offsets are still purchased even when they cost $200/t$CO_2$. This observation along with the results in Figure 2.6 indicate that actually eliminating the last few percent of emissions is very expensive on the margin.

2.4.2 CO_2 emissions

Figure 2.7 shows annual CO_2 emissions in the Baseline and Climate Plan (10% carbon offset allowance) scenarios, broken down into power and transportation. In the Baseline, total emissions continue to rise until 2038, then decline thereafter. The reductions in later years are confined to the power sector. The Climate Plan total emissions trajectory follows the policy constraint. Figure 2.7b exhibits a striking decarbonization pattern with two distinct stages. The power sector is decarbonized first, with transportation emissions only beginning to decline significantly around 2040 when very little CO_2 remains in electricity. This decarbonization sequence, advancing from power to transportation over time, is consistent with prior modeling results at higher spatial scales (Löffler et al., 2017; Pietzcker et al., 2014) and the notion that transportation exhibits strong carbon lock-in (Seto et al., 2016). Austin should focus near-term decarbonization efforts on the power sector (as it is currently doing through Austin Energy), knowing that transportation emissions will need to be addressed in the future once alternative fuel vehicles are cheaper and upstream emissions are lower. This lesson is likely generalizable to most cities.

2.4.3 Power

Figure 2.8 illustrates how the electricity generation mix evolves over time in the Baseline and Climate Plan scenarios. In both cases, there is no new investment in coal power plants. This is significant since coal plants are responsible for 84% of power sector emissions and 53% of all emissions in

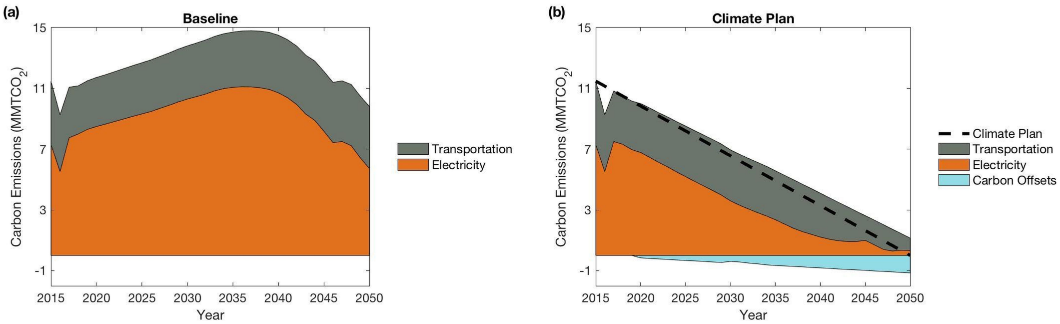

Figure 2.7. Annual CO_2 emissions in the Baseline (a) and Climate Plan (b) scenarios, broken down into power and transportation. Carbon offset purchases appear as a negative area because they contribute to satisfying the Climate Plan constraint (dashed black line).

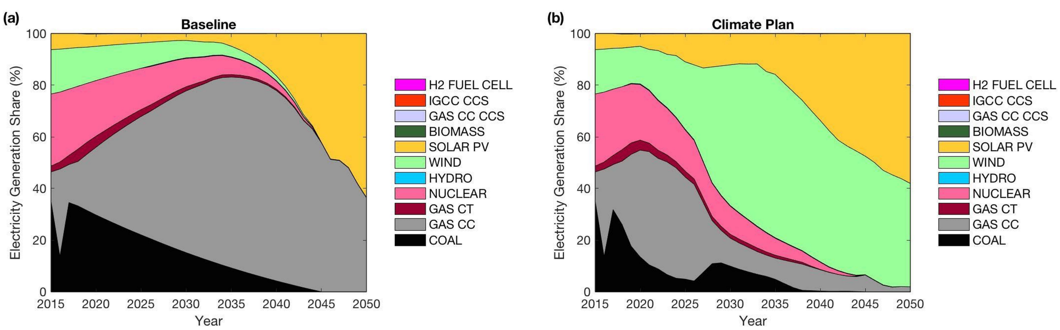

Figure 2.8. Evolution of the electricity generation mix in the Baseline (a) and Climate Plan (b) scenarios.

the 2015 base year.

In the Baseline scenario, GAS CC capacity is continually added through 2036. It is clearly the technology of choice in the near-term, matching the current trend favoring natural gas in the U.S. power sector. The GAS CC

Coal-fired electricity generation experiences a sharp dip in 2016 due to the natural gas price forecast, which returns to a forecast price of \$2.95/MMBtu in 2016 after an observed price of \$3.22/MMBtu in the 2015 base year. This explains the noticeable kink in Figures 2.7 and 2.8 at 2016.

generation share begins at approximately 11% in 2015, reaches a peak of 75% in 2039, then declines to its terminal value of 36% in 2050. Optimistic projections for future solar PV costs make it the preferred generation technology in the later years even in the absence of climate policy. By 2050, solar PV accounts for 64% of total generation, with the rest fueled by natural gas. Due to its lower capacity factors, solar PV actually occupies 83% of the terminal capacity mix.

The early years of the Climate Plan scenario see substitution of GAS CC generation for coal electricity, which drops to 4% of the total by 2027 and is completely phased out by 2045 despite a brief utilization resurgence prior to 2030 to accommodate rapid growth of intermittent wind and solar. Wind and solar PV expand aggressively, so much so that they begin displacing GAS CC generation in 2026. This sequence confirms the role of natural gas as a transition fuel in the power sector, aiding decarbonization in the near-term by substituting for coal, but ultimately giving way to renewables once the emissions target intensifies and renewables become more cost-competitive. After the initial years, renewables increasingly dominate the generation mix, and the 2050 mix consists of 40% wind and 58% solar PV (with GAS CC reduced to 2% of generation).

The rapid growth of solar PV begins sooner in the Climate Plan scenario than in the Baseline, but its overall outlook is bullish in either case due to favorable cost projections. Interestingly, the policy context has the biggest impact on the competition between GAS CC and wind for the rest of the future generation mix. The renewable portion of 2050 generation in the Baseline is entirely solar PV with no wind. In contrast, the 2050 Climate Plan mix incorporates substantial wind generation. The reasoning is that when renewable penetration is very high, the temporal complementarity between wind and solar PV is very valuable for ensuring that loads can be satisfied. Wind capacity factors in Texas are highest at night when solar PV is unavailable. The picture that emerges is that, in this setting, whether wind and solar PV are substitutes or complements depends on the total share of renewable generation.

It should be noted that total installed capacity in 2050 is greater in the Climate Plan scenario (25.6 GW) than in the Baseline (20.0 GW). This is a consequence of the comprehensive transition to intermittent renewable electricity technologies in the former, which have lower capacity factors than GAS CC. Indeed, by 2050, solar PV and wind capacities are 18.22 GW and 6.82 GW, respectively.

2.4.4 Transportation

Figure 2.9a reveals that private transportation in the Baseline scenario continues to be dominated by gasoline vehicles through 2050. Unlike the power sector, which eventually begins to decarbonize driven by purely economic considerations even in the absence of climate policy, the transportation sector appears unlikely to undergo major change without a policy stimulus. The Climate Plan results in Figure 2.9b show that electric vehicles are the most cost-effective technology for decarbonizing private transportation. Their adoption is initially slow and electric vehicles still only account for 4% of the market in 2030. Once the focus of decarbonization shifts from power to transportation, however, electric vehicles diffuse rapidly. They reach 24% market share in 2040 and a much larger 80% in 2050.

The public transportation mix evolves almost identically in the Baseline

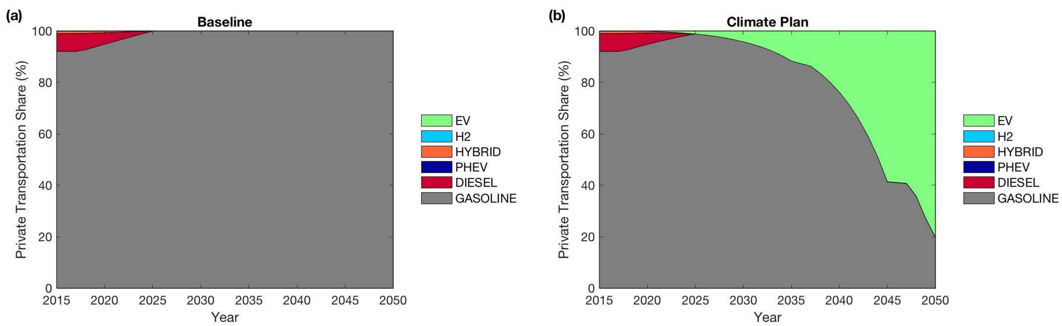

Figure 2.9. Evolution of the private vehicle mix in the Baseline (a) and Climate Plan (b) scenarios.

and Climate Plan scenarios, as shown in Figure 2.10. In both cases the fleet shifts strongly to biodiesel buses, which are evidently the most cost-competitive option given our cost and performance assumptions. Public transportation does not respond to the policy because the extreme capital cost differential between carbon-free bus technologies and biodiesel is too large to surmount. The public transportation demand is small but expensive to decarbonize, so carbon offset purchases are allocated first to public transportation, second to the remaining 20% of private transportation that is still fueled by gasoline, and lastly to the 2% of electricity generation that is still fueled by natural gas.

2.4.5 Demand response, energy storage, and electric vehicle charging

Figures 2.11 and 2.12 show the optimal seasonal electricity dispatch results for 2020 and 2050, respectively. The subfigures compare the Baseline (left column) and Climate Plan (right column) scenarios. In addition to power plant dispatch, they depict demand response, battery electricity storage charging and discharging, and electric vehicle charging. V2G deployment is not selected as part of the optimal transformation pathway in either scenario. Demand

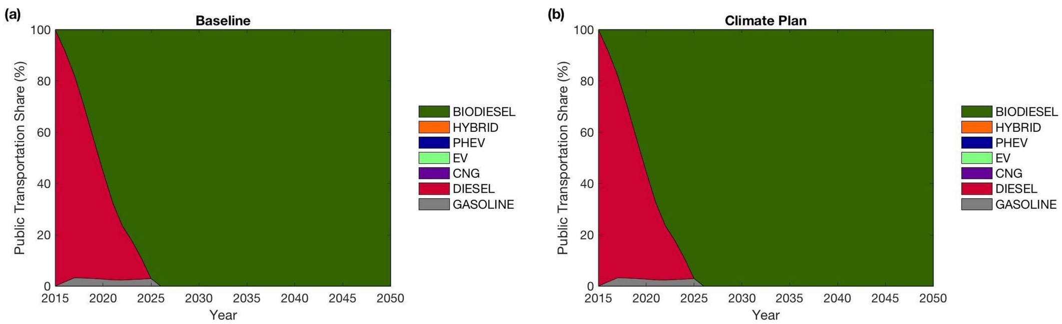

Figure 2.10. Evolution of the public vehicle mix in the Baseline (a) and Climate Plan (b) scenarios.

response and storage discharging appear as areas above the x-axis, since they effectively contribute to meeting the exogenous electrical loads (represented by the dotted black lines). Storage charging and electric vehicle charging appear as areas below the x-axis, since they add to the exogenous electrical loads. Figures 2.11 and 2.12 therefore reveal how the ability to intelligently schedule and coordinate demand response, energy storage, and electric vehicle operations facilitates cost-effective decarbonization.

Demand response does not feature prominently in the dispatch results for either year, though a small amount of demand response is called upon to meet the summer peak electricity demand in 2020 in the Baseline scenario. Nevertheless, the availability of demand response plays a major role in satisfying the two extreme hour constraints and thus ensuring that the system can cope with a particularly high load or a lack of renewable generation. This is not visible in the dispatch results for the representative seasonal days. The main benefit of demand response is therefore to reduce investment in additional peaking capacity rather than to save money on operating costs.

Energy storage plays a crucial role in the long-term evolution of Austin's

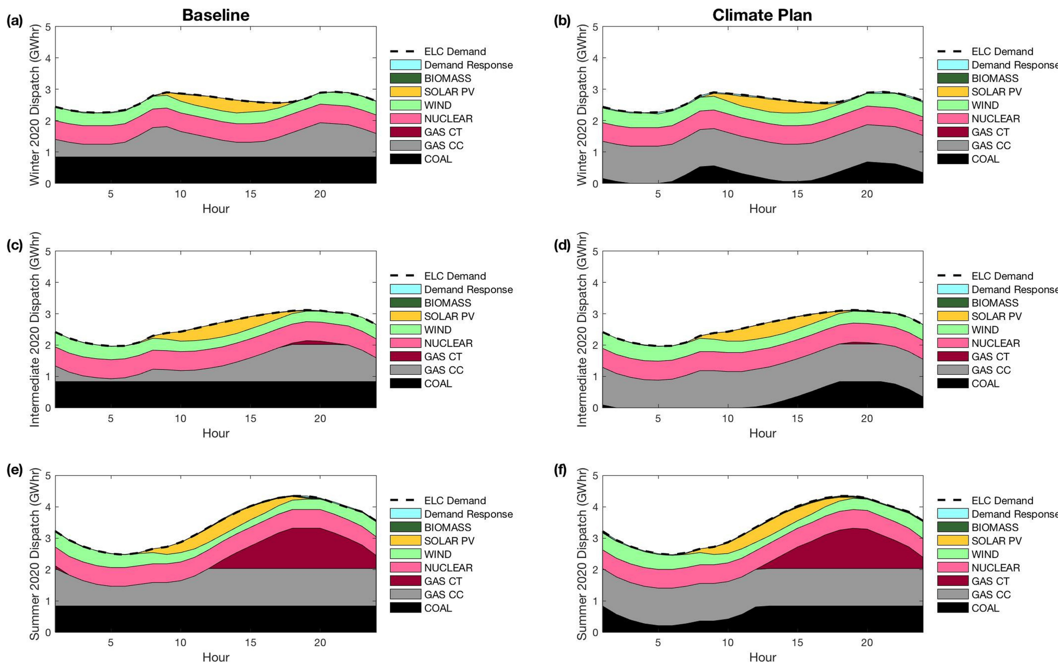

Figure 2.11. Seasonal power sector dispatch results for 2020 in the Baseline (left column) and Climate Plan (right column) scenarios. Dotted black lines represent exogenous electrical loads, which do not include demand response (teal area).

energy system. The Baseline transformation pathway includes 28 GWh of battery storage capacity by 2050. The Climate Plan (10% carbon offset allowance) induces further deployment of battery storage, reaching 36 GWh of capacity by 2050. At the end of the timeframe, solar PV makes up a substantial share of generation in both the Baseline and Climate Plan scenarios. In this context, optimal battery operation essentially follows the availability of solar PV. All the 2050 dispatch profiles in Figure 2.12 feature battery charging during the day when solar PV is abundant, and discharging to satisfy the exogenous load at night when solar PV is unavailable.

The electric vehicle charging results in the right column of Figure 2.12

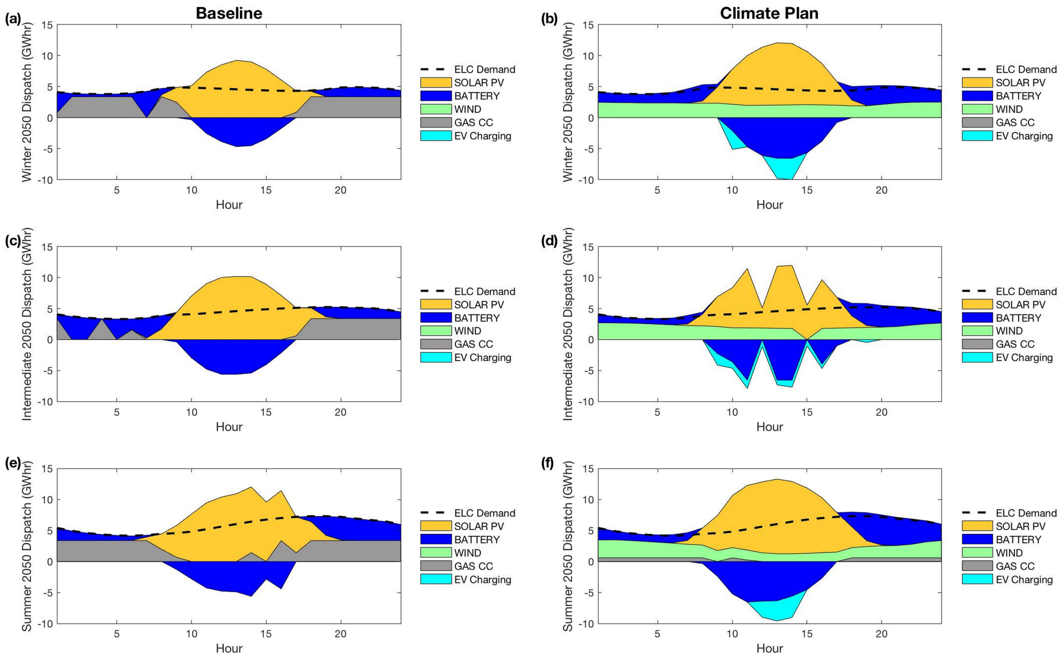

Figure 2.12. Seasonal power sector dispatch results for 2050 in the Baseline (left column) and Climate Plan (right column) scenarios. Dotted black lines represent exogenous electrical loads, which do not include battery storage charging (blue area below x-axis), battery storage discharging (blue area above x-axis), or electric vehicle charging (teal area below x-axis).

demonstrate another synergy between power and transportation under the ACCP. Similar to how batteries charge in a context of high solar PV penetration, optimal electric vehicle charging takes place over the daytime hours when solar PV is abundant. In reaching this outcome, our model implicitly assumes that there are no temporal restrictions on electric vehicle charging, and that charging infrastructure is widely available. We thus interpret our findings to imply that, as the power sector incorporates more solar generation, it will become increasingly important to provide electric vehicle charging infrastructure at workplaces so that coordinated charging can be aligned with solar power output.

Finally, although the jagged pattern of solar PV generation in Figure 2.12d may appear strange, it simply reflects the abundance of solar PV capacity relative to the demand for electricity in the intermediate (spring/fall) season. There is more than enough solar PV capacity to meet load, charge battery storage, and charge electric vehicles during the daytime, and none of these activities entails variable cost. So, the model can choose from a variety of dispatch schedules during the daytime hours that all result in the same objective value; the pattern observed in Figure 2.12d is one of these.

2.4.6 Public transportation and charging cost scenarios

In the Public Transportation scenarios, biodiesel buses remain the technology of choice for public transportation. However, with the modal shift toward public transportation, gasoline vehicles remain the dominant technology for private transportation, albeit steadily decreasing to 54% of the private vehicle fleet in 2050 (the rest of which is electric). Since VMT ultimately decline by 50% in the Public Transportation case, it is less critical to deeply decarbonize private transportation. Also, since the higher occupancy of buses means that ten VMT convert into one PM, there are far fewer total vehicles and total vehicle miles in the Public Transportation scenarios. This leads to substantial cost savings in terms of both the absolute net present energy system costs as well as the additional cost of the Climate Plan relative to the Baseline. In the Public Transportation setting, the net present cost is roughly $75.5 billion in the Baseline scenario and $77.3 billion in the Climate Plan scenario. The comparable objective values in the main scenarios were $89.0 billion and $91.4 billion. The policy cost of the Climate Plan beyond

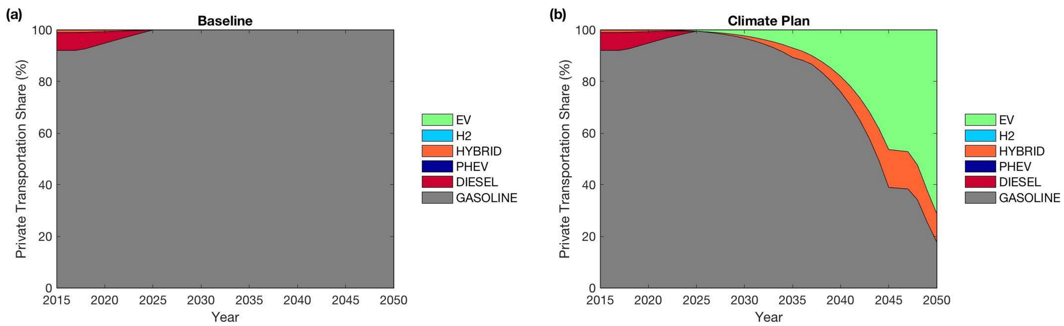

Figure 2.13. Evolution of the private vehicle mix in the Baseline (a) and Climate Plan (b) scenarios, with battery charger costs included

that of the Baseline thus decreases from \$2.4 billion (2.7% in relative terms) to \$1.8 billion (2.4% in relative terms) due to the transition toward public transportation. As previously stated, these benefits stem from the reductions in total vehicles and total vehicle miles enabled by the higher occupancy of buses, rather than changes in the public transportation technology mix. Of course, this Public Transportation setting is entirely hypothetical, and it would likely require major investments in public transit coupled with more compact or transit-oriented land use. It does demonstrate, however, the significant benefits that could result from such a modal shift.

In the Charging Cost scenarios, we include the costs of charging stations and associated installations that consumers typically incur when they purchase electric vehicles. We see no change in the public vehicle fleet, because electric buses were not even chosen in the main scenarios. However, in the Climate Plan scenario, the Charging Cost induces a resurgence of hybrid vehicles in the private vehicle mix beginning around 2030. As Figure 2.13b shows, hybrid vehicles later reach a maximum share of 15% in 2045. In the final years of the timeframe, the CO_2 constraint becomes stringent enough that additional hybrid investments are no longer tenable, and electric vehicles increasingly dominate despite added costs for chargers and their installation. Net present energy system cost under the Climate Plan is roughly \$0.4 billion higher in the Charging Cost setting than with the main set of assumptions.

2.5 Conclusion

We developed an energy system optimization model in the OSeMOSYS framework to determine cost-effective decarbonization pathways at the urban scale. For our case study, we used the model to evaluate the Austin Community Climate Plan (ACCP), which establishes a goal of net-zero GHG emissions by 2050. As a member of the C40 Cities Climate Leadership Group with a rapidly growing population and a particularly ambitious climate plan, Austin serves as a valuable testbed for analysis. Our findings thus contribute much-needed insights on how cities can develop sound climate policies and implement effective mitigation strategies. Furthermore, the OSeMOSYS platform we extend is an open source tool, and our hope is that more municipal agencies will employ energy system models to assess potential policy prescriptions.

We find that the ACCP increases net present power and transportation costs by 2.7% relative to business-as-usual. This economic impact is not trivial, but it does demonstrate that even the particularly ambitious net-zero emissions by 2050 goal can be achieved at modest cost. The optimal decarbonization pathway consists of two sequential stages: the power sector is decarbonized first, then the focus shifts to transportation. The ACCP hastens the elimination of coal from the power sector, initially through substitution by natural gas, but increasingly via the expansion of renewables. Solar PV actually comprises a majority of the 2050 generation mix even in the absence of climate policy, based on optimistic cost projections alone. The primary long-run impact of the ACCP on electricity is the replacement of natural gas with wind, which is an effective complement to solar PV under high renewable penetration due to their contrasting temporal profiles (wind at night, solar PV during the day). Once electricity decarbonizes, private transportation transitions to electric vehicles, which are less costly in these later years. Capital cost differentials between carbon-free and conventional options are more extreme in public transportation, which is therefore insensitive to the policy context, even under a scenario of significant modal shift from private to public transportation. Intelligent and coordinated scheduling of battery electricity storage and electric vehicle charging play important roles in the low-carbon transition. Battery storage charges during the daytime when solar PV is abundant and discharges at night when solar PV is unavailable. Optimal electric vehicle charging also occurs during the daytime to align with solar PV availability, which implies that making charging infrastructure available at workplaces would provide substantial system-wide value. Our model does not select V2G or hydrogen technologies in its optimal decarbonization pathways.

Of course, these findings must be interpreted in light of the limitations of the model and database. Our framework has a supply-side focus that does not explicitly incorporate demand-side decarbonization levers (except for demand response) such as end-use appliance efficiency, building efficiency, or urban land-use regulation. Seasonal 24-hour profiles represent intermittent renewable resources and fluctuating demands at higher resolution than most examples in the literature, but they still cannot capture the full range of variability that exists in reality. Due to a lack of available data, our database does not include smaller sources of Austin emissions such as industrial processes, direct natural gas consumption for heating, or landfills. There is not, however, a methodological limitation that precludes modelers from including such technologies. Exogenous parameter assumptions become more uncertain as the analysis timeframe approaches its 2050 horizon. The optimization algorithm assumes perfect foresight, which masks these uncertainties and is known to influence model results (Wilkerson et al., 2015).

Our research team has continued to develop these energy system optimization tools to address these limitations. For example, Leibowicz et al. (2018) consider end-use technology options for satisfying *disaggregated* energy service demands in the building sector, such as space heating and cooling, water heating, and lighting. In addition to both supply- and demand-side decarbonization levers, the authors consider how building thermal efficiency upgrades reduce space heating and cooling demands, thus exploiting important synergies within a comprehensive portfolio of emissions mitigation strategies. For example, the authors find that upgrading to a LEED Gold standard of building thermal efficiency reduces the cost of a climate policy by 37% compared to a case of no improvement in buildings' thermal efficiency. Jayadev et al. (2020) explore electricity infrastructure pathways from the present to 2050 and derive policy-relevant insights. And Jones and Leibowicz (2019) distinguish shared autonomous vehicles from privately owned vehicles to explore the contributions of shared autonomous vehicles to climate change mitigation. These additional features allow us to analyze a broader portfolio of mitigation strategies, though obtaining accurate data at the urban scale is always a formidable challenge.

In the context of this dissertation, our optimization framework does not capture other drivers of adoption besides cost considerations that arise from complex phenomena that exist in technology transitions. Indeed, in our energy system optimization model, once a technology becomes cost-effective it is adopted. For example, among the available vehicle technologies in the Austin, TX database, factors hypothesized to be influential in adoption decisions, such as individuals' sensitivities to EV charging times and range preferences, are not modeled. In the following chapters, we take a step back and develop high-level, theoretical models of technology transitions to address these shortcomings.

Despite its limitations, this study has contributed much-needed research on city climate plans and urban-scale mitigation pathways. We hope that our insights will provide helpful policy guidance for municipal governments as cities take on a more prominent role in climate change mitigation.

2.6 Acknowledgments and notes

Benjamin Leibowicz contributed to the conceptualization of the topic and provided the base GAMS code, which was then extended here. A version of this chapter has been published in *Sustainable Cities and Society* (Brozynski and Leibowicz, 2018), and we acknowledge the excellent comments and suggestions from two anonymous reviewers. We thank Zach Baumer, Climate Program Manager for the City of Austin, for sharing his insights about the development and execution of the Community Climate Plan.

Chapter 3

Markov models of policy support for technology transitions

3.1 Introduction

Many governments aim to promote the development and diffusion of new technologies such as renewable energy sources, medical treatments, agricultural innovations, and alternative fuel vehicles. Economic theory generally suggests that government intervention is justified in cases of market failure, including externalities and informational asymmetry. In the more specific context of policy support for new technologies, Salmenkaita and Salo (2002) summarize three key policy rationales: market failure (underinvestment in research and development (R&D) because firms are unable to capture all the benefits of innovation, so private benefits are smaller than social benefits), systemic failure (coordination problems among R&D players with different incentives), and structural inertia (path-dependence and feedbacks hamper the pursuit of new technologies). Technology policy is also viewed as a means of addressing negative externalities that often go unpriced in the market, such as greenhouse gas emissions that cause climate change (Nemet and Kammen, 2007).

Globally, governments collectively spend trillions of dollars per year on

Benjamin Leibowicz contributed to the conceptualization of the topic. A version of this chapter has been published in *European Journal of Operational Research* (Brozynski and Leibowicz, in press).

R&D efforts and incentives for consumers to adopt new technologies. However, designing policies that effectively stimulate technology transitions and generate net benefits is extremely challenging due to the highly complex and uncertain nature of technological change. Technology transitions, which Geels (2002) defines as "major technological transformations in the way societal functions ... are fulfilled," are demonstrably complex processes involving simultaneous change along technological, economic, institutional, social, and behavioral dimensions, which must be aligned for a technology transition to occur. Outcomes are impossible to predict in advance. R&D is an inherently risky enterprise, and even when a technologically superior alternative does arise, its success in the market is not guaranteed. The difficulty of designing technology policies is borne out by the erratic historical record. Some past government campaigns to promote technology transitions have been lauded as tremendous successes, such as the swift adoption of hybrid seed corn driven by agricultural extension agencies in the U.S. (Griliches, 1957), or the creation of a leading wind turbine industry in Denmark (Klaassen et al., 2005). On the other hand, there have been a number of very expensive failures, including the U.S. Synthetic Fuels Corporation established to reduce dependence on imported fossil fuels during the oil crisis (Anadon and Nemet, 2014), or the French effort to deploy fast breeder nuclear reactors (Grubler, 2012).

There is a rich, interdisciplinary literature on technology transitions, most of which consists of retrospective case studies, empirical data analyses, and qualitative frameworks. Early on, researchers including Ryan and Gross (1943), Coleman et al. (1957), and Griliches (1957) began to formalize the study of technology diffusion as a complex process that plays out gradually across communities of heterogeneous, interacting agents. Everett Rogers (1962) synthesized and popularized these ideas in his seminal book *Diffusion of Innovations*, and distilled from existing case studies some lessons for how governments and firms can purposefully accelerate diffusion. Through his case study of the QWERTY keyboard layout, David (1985) demonstrated that society can become locked-in to inferior technological regimes due to chance events that get amplified by increasing returns. These concepts have become central to policy studies and debates in diverse domains. In energy and climate change, many case studies continue to draw policy insights from past successes and failures (Grubler and Wilson, 2013), and scholars frequently suggest how technology policies should be designed to overcome carbon lock-in and accelerate sustainability transitions (Seto et al., 2016; Unruh, 2000, 2002). Ambitious researchers have attempted to integrate the insights obtained through case studies into unified conceptual frameworks, such as the multi-level perspective for understanding socio-technical transitions (Geels, 2002, 2005).

While these empirical case studies and qualitative conceptualizations have advanced our understanding of technology transitions, they have limited relevance as guides for making technology policy decisions under uncertainty. They rely on an inductive logic that attempts to establish qualitative, policy-relevant insights through the synthesis of case studies of specific experiences across myriad application domains and contexts. Indeed, poorly designed technology policy, intending to correct a market or systemic failure, may instead create a government failure, in which case the intervention actually causes further economic inefficiency (Stiglitz, 2009). What the literature largely lacks is a quantitative, theoretical modeling framework capable of yielding generalizable guidance for technology policy decisions. Our present work addresses this research gap. To ensure generality and analytical tractability, our models are necessarily quite abstract as presented. Undoubtedly, they omit many factors and details which would be important considerations in any real-world application. However, despite these shortcomings, our case study on lithium-ion batteries demonstrates that our approach can support practical policy decisions. Therefore, we view our theoretical framework and the policy insights we derive from it as complementary to the existing literature, and believe they represent a significant step toward a quantitative, integrated theory of technology transitions and the role of policy.

In this chapter, we develop a theoretical framework for evaluating technology policy interventions under uncertainty that yields highly general, analytical results. The decision maker we primarily envision is a government body considering spending public funds to promote the diffusion of a new technology. In a cost-benefit approach, we explore the circumstances under which the social benefits of intervention exceed the costs. Nevertheless, our models are flexible enough to offer relevant insights to other decision makers with a vested interest in the successful development or diffusion of a new technology, such as a firm considering spending money on product development or advertising to disseminate a new product throughout the market.

We adopt a top-down perspective and construct two Markov models of technology transitions that incorporate policy support decisions. The first model is a Markov reward process (MRP) where technology policy intervention requires a one-time, upfront cost. The second is a Markov decision process (MDP) where technology policy incurs a cost every time the process is in a state targeted by the policy. In our analysis of both models, we focus on the policymaker's willingness to pay (WTP) for portfolios of technology policies that improve the probabilities of the technology transition advancing at different stages. We find that the two models share intuitive similarities, but that the behaviors of their optimal decision rules diverge due to their different cost accounting mechanisms. More generally, our most fundamental contribution to the literature is to bring an operations research approach to technology policy analysis and offer a theoretical framework capable of producing general, analytical, decision-relevant insights.

The remainder of this chapter is organized as follows. In Section 4.2, we review the existing literature on models of technology transitions, diffusion, and policy, and highlight the similarities and differences between these previous studies and our analysis. We present our MRP and MDP models in Section 4.3 and derive key analytical results in Section 3.4. The numerical examples in Section 3.5 demonstrate how our framework can be used to determine the optimal technology policy portfolio, and allow us to explore how the optimal portfolio varies with certain parameters. In Section 4.5, we demonstrate the practical application of our models by conducting a case study on lithium-ion batteries for electric vehicles. We conclude in Section 3.7 with a summary of our most important findings and contributions to the literature.

3.2 Literature review

We review four branches of the literature in the following four subsections: (1) top-down stochastic models of technology diffusion, (2) bottom-up stochastic models of technology diffusion, (3) economic models of optimal technology policy intervention, and (4) large-scale numerical policy analysis models featuring technology policies.

3.2.1 Top-down stochastic models of technology diffusion

Top-down models of technological change represent technology dynamics using aggregate measures like market shares of competing alternatives as the endogenous variables. Rogers (1962) popularized the use of logistic diffusion curves to model the cumulative adoption of an innovation over time. In the operations research literature, a pioneering and highly influential contribution was the Bass Model (Bass, 1969). In this formulation, the fraction of remaining potential adopters who adopt an innovation at a given time is a linear function of the number of previous adopters. The model thus captures the inertia by which technology diffusion initially accelerates, then slows down as the market saturates. Bass derives analytical results for key properties of a diffusion process (e.g., peak sales time, expected adoption time) and shows that the model fits empirical data on consumer durables quite well. Many extensions of the Bass Model appear in the literature, such as versions with marketing decision variables (Bass et al., 1994), multiple product generations (Jiang and Jain, 2012; Norton and Bass, 1987), or stochastic demand (Niu, 2006).

While Bass (1969) describes the aggregate behavior of his model as being driven by probabilistic adoption decisions at the individual level, his model is ultimately a deterministic one. The formal analysis of technological change as a stochastic process was really initiated by W. Brian Arthur, whose widely cited top-down models are similar to our own in that they feature uncertainty in the technology transition pathway, such as how market shares will evolve.

Arthur et al. (1987) formulate and analyze a nonlinear Polya urn process model that captures the path-dependency of technological competition due to increasing returns. In the standard Polya process, the probability that the next adopter will choose technology A is equal to A's current market share. The nonlinear Polya process is a generalization in which technological competition is governed by adoption probabilities that are arbitrary functions of the current market shares. The authors prove that the market shares in a nonlinear Polya process will eventually converge to a stable fixed point of the urn function, as is the case in the standard Polya model. Arthur and Lane (1993) use this nonlinear Polya process framework to study the effect of increasing returns via an information contagion mechanism. Information contagion is the phenomenon by which prospective adopters supplement publicly available information about competing technologies with private information obtained by sampling past adopters of these technologies. The authors prove that the probability that the next purchase will be technology A, for example, is given by a polynomial urn function of A's current market share, which settles to a stable fixed point of this urn function. Notably, the outcome can be complete dominance by one technology even if all competing technologies are identical. Which technology comes to dominate is not predictable ex ante.

Arthur (1989) represents the competition between two technologies, A and B, as a sequence of adoption decisions made by two types of agents. The benefit that each agent type derives from a technology is a linear function of the number of previous adopters of that technology, with the constant terms reflecting initial preferences of agent types A and B. An agent type is selected with equal likelihood in each period, and adopts the technology that gives her the higher benefit. Arthur shows that under increasing returns (i.e., benefits increase in the number of previous adopters), this stochastic model has some daunting consequences for trying to predict technological outcomes or ensure economic efficiency. The evolution of the market is non-ergodic in that small chance events tip the allocation toward one dominated by a single technology, instead of being averaged away. There is a risk of becoming locked-in to a technology pathway with inferior long-run benefits if there is an early streak of agents who prefer an initially appealing but slow-to-improve technology.

Similar to these previous formulations, our models are top-down, dynamic, stochastic representations of technological change. Our framework goes beyond these earlier treatments by explicitly incorporating technology policy decision making under uncertainty. This allows us to obtain decision rules about optimal policy intervention rather than merely establish the properties of a stochastic diffusion process.

3.2.2 Bottom-up stochastic models of technology diffusion

One branch of the operations research literature models technology diffusion as a stochastic process, but from the perspective of the individual agents making adoption decisions. Like ours, these bottom-up models focus on decision making under uncertainty, but the decisions being analyzed are the strategic adoption choices of individual agents in the market rather than a technology policy decision. The studies discussed below examine the structure of optimal technology adoption decisions and explore how optimal decisions are affected by model parameters.

Kornish (2006) constructs a model where an individual considers a choice between two competing technologies that are both subject to positive network effects. In each period, the individual either adopts one of the technologies, or opts to wait. While this individual's decisions are explicitly modeled, the behavior of other agents in the market is represented as a nonlinear Polya urn function (Arthur et al., 1987). Committing to a technology entails a key tradeoff. It is better to begin deriving benefits sooner rather than later, but by waiting, the individual can observe which technology is proving to be most popular and thus capture its positive network effects. Kornish finds that the optimal strategy is of a threshold type with respect to the number of previous adopters of each technology. She then explores how stronger network effects influence the optimal strategy.

Several more recent papers also model individual technology adoption decisions, but do not focus on the implications of increasing returns for the competition among technologies. Instead, these papers emphasize the role that information gathering plays in the adoption process of a single (or sometimes dependent) technology. Employing a real options approach to the timing of adoption decisions, this literature seeks to understand why superior technologies historically suffer from slow or incomplete adoption. McCardle (1985) considers a firm's adoption decision on a new technology with uncertain profitability. The firm will optimally gather information to reduce the level of its uncertainty about the technology's profitability until an adopt or reject threshold is met. Interestingly, it is possible for an optimally-behaving firm to adopt a technology that is ultimately unprofitable. Farzin et al. (1998) assume that a technology advances according to a compound Poisson process, and uncover the existence of a threshold-based optimal policy. Huisman (2001) analyzes several adoption models in which the income stream to a firm follows a geometric Brownian motion. Cho and McCardle (2009) extend real options models to the case in which multiple dependent technologies are evolving, showing that the economic dependencies that define cost relationships within the firm, in addition to uncertainties beyond the firm, can significantly influence the timing of adoption. Ulu and Smith (2009) analyze a sequential decision problem in which an individual chooses to adopt a new technology, reject it, or wait under uncertain benefits. When she decides to wait, she obtains a new distribution on the benefits via Bayesian updating. The authors show that a better technology may not actually make the consumer better off once the costs of information gathering and the adoption process are taken into account. Smith and Ulu (2017) extend their earlier analysis by investigating how risk aversion affects the optimal adoption strategy. Finally, Smith and Ulu (2012) compare and contrast three models (NPV, single-purchase, and repeat-purchase) of an individual's technology adoption decision under uncertain future costs and quality, modeled as Markov process transitions. They find that in the repeat-purchase or "upgrades" model, technological improvements that make the consumer better off may also discourage adoption.

We emphasize that, while models of technology adoption decisions are well-established in the literature, they do not directly inform technology policy decision making. Adopters and policymakers face different decisions and usually have different objectives. Instead, our work leverages Markov modeling to inform technology policy decision making from the perspective of a policy-maker.

3.2.3 Economic models of optimal technology policy intervention

Two branches of the economics literature feature models used to derive optimal technology policies. In general, compared to operations research models like ours, these economic models represent time and uncertainty in less detail (if at all), but consider more specific policy instruments, strategic competition among multiple firms, and welfare impacts. Their limited representations of time, but rich representations of innovating firms, make them better suited to assess supply-side technology policies like R&D subsidies than demand-side interventions intended to spur faster and more thorough adoption.

Optimal technology policies are explored in the industrial organization literature on R&D rivalry games. These models typically include two stages. In the first stage, competing firms make R&D investment decisions that affect their production costs in stage two, when they compete in the market by choosing production quantities. Leahy and Neary (1997) analyze optimal policy intervention in one such oligopoly model. They consider the first-best policy featuring both R&D and product subsidies, as well as the second-best policy featuring only an R&D subsidy. The authors determine that strategic behavior by firms justifies higher subsidies unless R&D spillovers are weak and firms' actions are strategic substitutes. Tishler and Milstein (2009) work within a similar framework, but incorporate new product R&D in addition to cost-reducing R&D, and add uncertainty by treating R&D outcomes as random variables. Between the two stages, firms observe the realizations of their R&D investments. The authors elucidate opposing forces with respect to competition and innovation: a strategic effect that increases R&D effort with competition and a demand reduction effect (due to competition among substitute products) that decreases R&D effort with competition. The implication is that firms may spend excessively on R&D to escape competition when rivalry is intense. Leibowicz (2018c) constructs a model featuring both cost-reducing and new product R&D with stochastic outcomes, similar to the model of Tishler and Milstein (2009). However, Leibowicz considers the implications of suboptimal policy magnitudes, and how far from optimal these policy levels can be yet still improve social welfare relative to the laissez-faire scenario.

A second branch of the economics literature that addresses optimal technology policy is endogenous growth theory. Based on earlier, highly influential models like those of Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992), subsequent authors have explicitly characterized optimal technology policy interventions within endogenous growth frameworks. Thompson and Waldo (1994) derive the optimal R&D subsidy in a model that allows firms to capture market share from rivals, but does not exhibit complete dominance by one firm. Segerstrom and Zolnierek (1999) analyze a quality ladder growth model in which vertical innovations can earn firms temporary monopolies on producing intermediate goods. If industry leaders and followers have access to different R&D technologies, then the optimal policy portfolio subsidizes R&D expenditures of all firms, subsidizes production of industry leaders, and taxes profits of followers. Furthermore, Thompson (2000) develops a multi-country model and shows that the optimal policy approach is an R&D subsidy for technological leaders but a tax on technological laggards.

3.2.4 Numerical policy analysis models

Numerical policy analysis models in various application domains feature technology policy decisions, sometimes under uncertainty. This is particularly true in the energy and climate policy modeling literature, from which the examples below are drawn. Integrated assessment models (IAMs) represent linked energy, economic, and earth systems to enable quantitative analysis of long-run energy and climate policies. Continued model development has led many IAMs to incorporate endogenous technological change. Some of these formulations include R&D investment decision variables, where R&D can lower the future costs of climate change mitigation. IAMs are large-scale models that must be solved numerically. They are domain-specific and produce results that are parmaterization-dependent. Therefore, unlike the more parsimonious models covered above, or our models in this chapter, IAMs do not yield analytical and generalizable results. Their technology policy decisions are embedded within much broader constellations of decision variables. Furthermore, while some IAM frameworks feature uncertain R&D outcomes, they do not incorporate uncertainty into the technology diffusion process.

Blanford (2009) develops an energy technology R&D decision framework in which an IAM is used to quantify the benefits of achieving various technology cost and performance levels. Given these benefits, Blanford determines the optimal portfolio of R&D investments, where increasing investment raises the probability of successfully achieving a cost or performance target. Baker et al. (2020) use robust portfolio decision analysis to identify energy technology R&D portfolios that are non-dominated over multiple sets of expert beliefs about probability distributions on R&D outcomes. Minimized cost objective values for achieving climate stabilization at 2°C are obtained from an IAM and used to establish the relative benefits of different R&D results. Bosetti et al. (2009) explicitly incorporate R&D decision variables into the World Induced Technical Change Hybrid (WITCH) IAM, and show that large energy R&D investments are required for the breakthrough innovation needed to mitigate climate change. Bosetti and Tavoni (2009) develop a version of WITCH where R&D effectiveness is stochastic, and find that this uncertainty justifies higher R&D investments and leads to lower climate policy costs.

3.3 Models

We formulate two closely related, but fundamentally different, Markov models of policy support for technology transitions. The first is a Markov reward process (MRP) and the second is a Markov decision process (MDP). Before we discuss the differences between the two models, we first describe their similarities.

Each model features discrete time, an infinite horizon, and a discrete state space. In fact, both models include the same three states corresponding to progressively more advanced stages in the diffusion or development of a technology.Indeed, our models can flexibly represent either the diffusion (tracked by market shares and adoption) or development (tracked by performance and cost characteristics) of a technology, or some combination of the two (i.e., performance and cost can be thought of as co-evolving with the diffusion process). State 1 is the initial state. For a diffusion application, State 1 could represent the stage when a technology is ready for commercialization, but has not yet achieved any appreciable level of market share. For a development application, State 1 could represent a relatively immature technology with poor performance and/or cost characteristics. State 2 is interpreted as an intermediate stage of the process, and State 3 represents the completion of the technology transition, saturating at either some maximum level of adoption (for diffusion) or final performance and/or cost benchmarks (for development). Implicitly, we assume that these levels of adoption or development of the technology are exogenously defined and known. To streamline our exposition of the models and analytical results in this section and the next, we primarily use the terminology associated with a technology diffusion process; however, we emphasize that our models apply equally well to technology development, as demonstrated by our case study in Section 4.5.

The stochastic process proceeds probabilistically through the states, via Markov process state transitions, and effectively ends when it reaches State 3, which is absorbing. It is possible to regress from State 2 back to State 1, which represents a technology that achieves limited market acceptance, never makes it to widespread diffusion, and ultimately fails. Remaining in State 1 can be interpreted either as a single technology taking more time to begin market penetration or improve its technical characteristics, or as the failure of one candidate technology followed by the emergence of another candidate. Regardless, the full process of beginning in State 1 and ending in State 3 represents one technology transition.

It is worthwhile to clarify that we depict three states simply because this is the smallest state space that allows us to address our questions of interest. In principle, there could be many more states in these Markov models to capture the technology transition process in greater resolution, including, for example, laboratory and prototype stages, where substantial public R&D funds are directed, in addition to an early commercialization stage. However, from our perspective, expanding the state space would make the analysis much more cumbersome without fundamentally altering the insights that can be obtained from the models. Furthermore, in a practical application, the definitions of the states are flexible as long as they are consistent; they are interpreted by the modeler based on the particular application and available data.

The policymaker receives a reward in each time period depending on the

---

In a technology development application, one might assume that the probability of regressing is zero (i.e., if a technology achieves better performance and cost, there is little reason to believe that this progress would be lost).

destination of that period's transition. More advanced stages of the diffusion process confer higher rewards. The policymaker's objective is to maximize the total expected discounted reward over an infinite horizon, incentivizing a faster progression from State 1 to State 2, and ultimately to State 3.

Policy interventions are represented in both models as paying for more favorable transition probabilities. Therefore, the policymaker must consider both the costs and benefits of intervention before determining whether it is justified. Note that we are not concerned with the particular form of the policy instrument, which could be a subsidy for consumer adoption, funding for cost-reducing or performance-enhancing R&D, or something else entirely. Since we focus only on the costs and benefits of policy intervention, our models are capable of considering a range of different policy instruments, resulting in a parsimonious and flexible modeling approach. Our analysis will focus on the WTP for policy interventions at various stages of the diffusion process. Characterizing the WTP helps decision makers determine at which stage(s), if any, policy is justified.

The fundamental distinction between the MRP and MDP models is the way they incorporate technology policy costs. In the MRP model, the policy cost is incurred once, upfront, as a lump sum payment. Essentially, the policymaker must compare the additional total expected discounted reward of the MRP under the (more favorable) policy parameterization of the transition probability matrix to the one-time cost of the policy. In the MDP model, policy costs are incurred every time the diffusion process is in a state targeted by the intervention. In reality, the MRP and MDP models are best suited to different types of policy instruments. For example, R&D investment which permanently enhances the performance of a technology seems well aligned

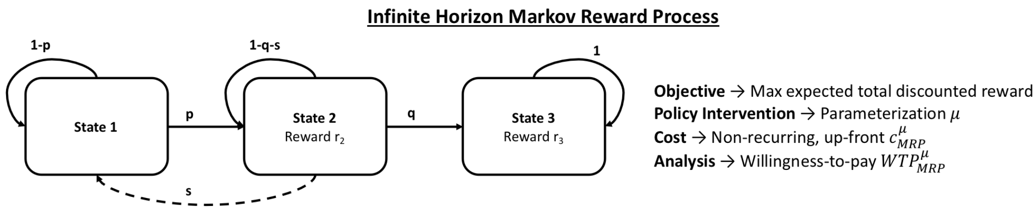

Figure 3.1. Diagram of our Markov reward process (MRP) model.

with the persistent effect of the one-time investment in the MRP, whereas an adoption subsidy during a particular phase of the technology life cycle seems to correspond better to the recurrent cost accounting of the MDP.

3.3.1 Markov reward process model

Figure 3.1 presents a diagram of our MRP model. Here, we explain the notation, then define the WTP in the MRP context.

Every realization of the diffusion process begins in State 1. With probability p, the process transitions from State 1 to State 2, or with the complementary probability $1-p$, the process stays in State 1 for an additional period. Once in State 2, the process transitions back to State 1 with probability s, transitions to State 3 with probability q, or remains in State 2 for an additional period with probability $1 - q - s$. We depict the transition from State 2 to State 1 with a dashed line because we also consider a special case where this transition cannot occur. State 3 is absorbing and thus represents the completion of the technology transition. For a value system, we associate rewards r_2 and r_3 with transitions to States 2 and 3, respectively, assuming that $r_3 > r_2$. The policymaker maximizes the total expected discounted reward of the MRP, with constant discount factor δ, minus the upfront cost of whichever policy intervention she undertakes.

Each possible policy intervention corresponds to a parameterization of the MRP's transition probability matrix, as well as the one-time policy cost. Let the set of possible policy interventions be denoted $M = \{\mu_0, \mu_1, \mu_2, \mu_{12}\}$, where $\mu_0 = \{p, s, q\}$, $\mu_1 = \{p', s, q\}$, $\mu_2 = \{p, s', q'\}$, and $\mu_{12} = \{p', s', q'\}$. Parameterization μ_0 represents the laissez-faire status quo of the system and has zero cost. The subscripts on the other elements of M indicate which transition probabilities change under selection of that policy intervention. For example, selecting policy intervention (parameterization) μ_1 increases the transition probability from State 1 to State 2 from the status quo probability p to the higher probability p'. We only consider policy probabilities that are more favorable than status quo probabilities, so that $p' > p$, $q' > q$, and $s' < s$.

To clearly distinguish our analysis of the MRP model from that of the MDP model, we let $v^{\mu_k}_{MRP}(i)$ denote the "value to go" at state i of the MRP under parameterization μ_k. Our analysis in the next section will focus on the quantity $WTP^{\mu_k}_{MRP}$, which is the willingness to pay for policy intervention μ_k in the MRP model. Definition 3.1 formally defines $WTP^{\mu_k}_{MRP}$.

Definition 3.1. $WTP^{\mu_k}_{MRP} = v^{\mu_k}_{MRP}(1) - v^{\mu_0}_{MRP}(1)$.

The policymaker's WTP for policy μ_k is thus equal to the difference between the total expected discounted rewards under policy μ_k and under the status quo μ_0 (which is equivalent to the difference between their values to go from State 1, where the process always begins). If the cost of policy μ_k

---

We do not consider a policy, for example, that improves the regressive transition probability s, but not also q, i.e. $\{p, s', q\}$. In order to limit the policy comparisons we make, we assume that policy intervention targeting a state affects all transition probabilities out of that state simultaneously. Perhaps in an extended case study, such "split" policies could be considered, despite the inherent difficulty in parameterization.

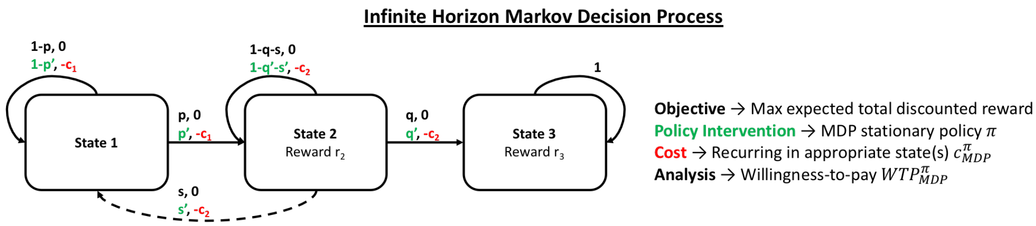

Figure 3.2. Diagram of our Markov decision process (MDP) model.

is below $WTP^{\mu_k}_{MRP}$, then policy μ_k is preferred to the status quo. Otherwise, policy μ_k is a suboptimal choice.

3.3.2 Markov decision process model

Figure 3.2 presents a diagram of the MDP model. Unlike in the MRP model, the set of policy interventions in the MDP is the set of infinite horizon stationary policies in the traditional MDP sense. This set is $\Pi = \{\pi_0, \pi_1, \pi_2, \pi_{12}\}$, where the subscripts have the same meaning as in the MRP model. Each of the policies is described by an underlying transition probability matrix as well as the costs of taking the specified policy actions every time the process is in an affected state. The policies are given by $\pi_0 = \{p, s, q\}$, $\pi_1 = \{p', s, q\}$, $\pi_2 = \{p, s', q'\}$, and $\pi_{12} = \{p', s', q'\}$ with associated costs $c^{\pi_1}_{MDP}$ in State 1, $c^{\pi_2}_{MDP}$ in State 2, and $c^{\pi_{12}}_{MDP}$ in both States 1 and 2, respectively. For example, under policy $\pi_1 = \{p', s, q\}$, the transition probability from State 1 to State 2 increases from p to p' and a cost $c^{\pi_1}_{MDP}$ (negative reward) is incurred every time the process is in State 1. Note that we assume that, for policy π_{12}, identical costs are incurred for policy intervention in States 1 and 2. For the same reason given above in the MRP model, we do not consider other possible policy combinations such as $\{p, s', q\}$.

We let $v^{\pi_k}_{MDP}(i)$ denote the value to go at state i of the MDP under policy

π_k. We are interested in the willingness to pay for a particular policy π_k, formalized in Definition 3.2.

Definition 3.2. $WTP^{\pi_k}_{MDP} = \{c^{\pi_k}_{MDP} : v^{\pi_k}_{MDP}(1) = v^{\pi_0}_{MDP}(1)\}$.

The policymaker's WTP for policy π_k is the recurring policy cost in all states affected by π_k that makes the policymaker indifferent between implementing this policy intervention or doing nothing (π_0). In other words, if the recurring policy cost associated with policy π_k is exactly $WTP^{\pi_k}_{MDP}$, then the total expected discounted reward under π_k will be the same as that under the status quo. If $c^{\pi_k}_{MDP} < WTP^{\pi_k}_{MDP}$, then the policymaker prefers policy intervention π_k to the laissez-faire approach. Otherwise, policy π_k is suboptimal. In the case of policy π_{12}, Definition 3.2 remains valid since the cost of policy action in State 1 is equal to the cost of policy action in State 2.

It is important to recognize that $WTP^{\mu_k}_{MRP}$ and $WTP^{\pi_k}_{MDP}$ are not directly comparable, since the two thresholds are defined differently due to the distinct cost accounting schemes of the MRP and MDP models. The former is a one-time, upfront cost, while the latter is the cost of policy actions within the MDP that can be incurred numerous times. However, our results reveal key similarities and differences between the two models, providing powerful insights into technology policy decision making with upfront or recurring costs.

While the interpretation of WTP in the MRP model is immediately intuitive, care should be taken when interpreting WTP in the MDP. For example, if the policymaker chooses policy π_1 in the MDP model, the policymaker does not in fact pay $c^{\pi_1}_{MDP}$, but a discounted random stream of $c^{\pi_1}_{MDP}$ in different periods. Regardless, analysis of the WTP allows a comparison among policies (principally, against taking no intervention) and a comparison between the MRP and MDP models themselves. In reality, as is demonstrated in the numerical analysis in Section 3.5 and the case study in Section 3.6, the optimal solution is obtained by comparing the expected total discounted reward under the four policy interventions.

3.4 Analysis

In this section, we first derive the WTPs in both models, then derive several key analytical results that describe the behaviors of both models and reveal important differences between them.

3.4.1 Analysis of the Markov reward process model

We start by deriving $WTP^{\mu_1}_{MRP}$, the amount the policymaker is willing to pay upfront for the policy intervention targeting State 1. We must first determine the State 1 value functions under parameterizations μ_0 and μ_1. The Bellman equations that define the value functions of the MRP under parameterization μ_0 are

$$\begin{cases} v^{\mu_0}_{MRP}(1) = pr_2 + \delta(1-p)v^{\mu_0}_{MRP}(1) + \delta p v^{\mu_0}_{MRP}(2), \\ v^{\mu_0}_{MRP}(2) = (1-q-s)r_2 + qr_3 + \delta s v^{\mu_0}_{MRP}(1) + \delta(1-q-s)v^{\mu_0}_{MRP}(2) + \delta q v^{\mu_0}_{MRP}(3), \\ v^{\mu_0}_{MRP}(3) = r_3 + \delta v^{\mu_0}_{MRP}(3). \end{cases} \tag{3.1}$$

Rewards are received upon transitions to States 2 and 3, and are discounted to the present by discount factor δ. By symmetry, we do not need to solve the other three sets of Bellman equations corresponding to parameterizations μ_1, μ_2, and μ_{12} separately, since the one-time policy cost does not directly affect the total expected discounted reward.

We solve the Bellman equations by substitution and obtain the analytical solution

$$v^{\mu_0}_{MRP}(1) = \frac{pr_2 + \delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta) + \delta p(1-\delta+\delta q)}. \tag{3.2}$$

Table 3.1. Analytical results for all WTPs in the MRP model.

	WTP	Result
General case	$WTP_{MRP}^{\mu_1}$	$\frac{(p'-p)(1-\delta+\delta q+\delta s)(r_2(1-\delta)+\delta qr_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))}$
	$WTP_{MRP}^{\mu_2}$	$\frac{(r_3-r_2)(q'-q)\delta p(1-\delta+\delta p)+\delta p(\delta r_3(q's-qs')-r_2(s'-s)(1-\delta))}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))}$
	$WTP_{MRP}^{\mu_{12}}$	$\frac{p'r_2+\delta p'q'r_3/(1-\delta)}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q')} - \frac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)}$
Special case	$WTP_{MRP}^{\mu_1}$	$\frac{(p'-p)(r_2(1-\delta)+\delta qr_3)}{(1-\delta+\delta p')(1-\delta+\delta p)(1-\delta+\delta q)}$
	$WTP_{MRP}^{\mu_2}$	$\frac{(r_3-r_2)(q'-q)\delta p}{(1-\delta+\delta q')(1-\delta+\delta q)(1-\delta+\delta p)}$
$(s = s' = 0)$	$WTP_{MRP}^{\mu_{12}}$	$\frac{p'r_2+\delta p'q'r_3/(1-\delta)}{(1-\delta+\delta q')(1-\delta+\delta p')} - \frac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q)(1-\delta+\delta p)}$

Then, we derive $WTP_{MRP}^{\mu_1}$ according to Definition 3.1, and the result is reported in Table 3.1. Intuitively, under our assumption that $p' > p$, $WTP_{MRP}^{\mu_1}$ is always positive. We also consider the special case in which the regressive transition from State 2 back to State 1 (dashed line in Figure 3.1) is not allowed (i.e., $s = s' = 0$). Table 3.1 includes the expression for $WTP_{MRP}^{\mu_1}$ under this special case as well.

Derivations of the WTP expressions for the other MRP policy interventions, which are procedurally analogous, are provided in the appendix. The analytical results for their WTPs in the general and special (i.e., $s = s' = 0$) cases are all included in Table 3.1.

3.4.2 Analysis of the Markov decision process model

We now proceed through the derivation of the WTPs in the MDP model. First, we consider $WTP_{MDP}^{\pi_1}$, the amount the policymaker is willing to pay for policy intervention targeting State 1, incurred every time the diffusion process is in State 1. We must first determine the value functions of the MDP under policy π_0, given as the solution to the Bellman equations

$$\begin{cases} v^{\pi_0}_{MDP}(1) = pr_2 + \delta(1-p)v^{\pi_0}_{MDP}(1) + \delta p v^{\pi_0}_{MDP}(2), \\ v^{\pi_0}_{MDP}(2) = (1-q-s)r_2 + qr_3 + \delta s v^{\pi_0}_{MDP}(1) + \delta(1-q-s)v^{\pi_0}_{MDP}(2) + \delta q v^{\pi_0}_{MDP}(3), \\ v^{\pi_0}_{MDP}(3) = r_3 + \delta v^{\pi_0}_{MDP}(3). \end{cases} \tag{3.3}$$

Because stationary policy π_0 represents the status quo of the system, it has no associated costs, and the solution to the Bellman equations is the same as it was in the MRP model under parameterization μ_0 (see Eq. (3.2)).

We solve the Bellman equations for $v^{\pi_0}_{MDP}(1)$, the total expected discounted reward when stationary policy π_0 is chosen and the process begins in State 1. Its solution is

$$v^{\pi_0}_{MDP}(1) = \frac{pr_2 + \delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta) + \delta p(1-\delta+\delta q)}. \tag{3.4}$$

Now we solve the Bellman equations associated with policy π_1,

$$\begin{cases} v^{\pi_1}_{MDP}(1) = -c^{\pi_1}_{MDP} + p'r_2 + \delta(1-p')v^{\pi_1}_{MDP}(1) + \delta p' v^{\pi_1}_{MDP}(2), \\ v^{\pi_1}_{MDP}(2) = (1-q-s)r_2 + qr_3 + \delta s v^{\pi_1}_{MDP}(1) + \delta(1-q-s)v^{\pi_1}_{MDP}(2) + \delta q v^{\pi_1}_{MDP}(3), \\ v^{\pi_1}_{MDP}(3) = r_3 + \delta v^{\pi_1}_{MDP}(3) \end{cases} \tag{3.5}$$

to determine the total expected discounted reward when stationary policy π_1 is chosen. Note that $c^{\pi_1}_{MDP}$ is the cost incurred under stationary policy π_1 whenever the process is in State 1.

We solve the system in Eq. (3.5) by substitution, obtaining the the total expected discounted reward when stationary policy π_1 is chosen and the process begins in State 1, $v^{\pi_1}_{MDP}(1)$, as

Table 3.2. Analytical results for all WTPs in the MDP model.

	WTP	Result
General case	$WTP^{\pi_1}_{MDP}$	$\frac{(p'-p)(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)}$
	$WTP^{\pi_2}_{MDP}$	$\frac{(q'-q)(r_3-r_2)(1-\delta+\delta p)+r_2(1-\delta)(s-s')+\delta r_3(q's-q's)(1-\delta+\delta p)/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)}$
	$WTP^{\pi_{12}}_{MDP}$	$\frac{(p'r_2+\delta p'q'r_3/(1-\delta))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))-(pr_2+\delta pqr_3/(1-\delta))((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))}{1-\delta+\delta q'+\delta s'+\delta p'}$
Special case ($s = s' = 0$)	$WTP^{\pi_1}_{MDP}$	$\frac{(p'-p)(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q)(1-\delta+\delta p)}$
	$WTP^{\pi_2}_{MDP}$	$\frac{(q'-q)(r_3-r_2)}{1-\delta+\delta q}$
	$WTP^{\pi_{12}}_{MDP}$	$\frac{(p'r_2+\delta p'q'r_3/(1-\delta))(1-\delta+\delta q)(1-\delta+\delta p)-(pr_2+\delta pqr_3/(1-\delta))(1-\delta+\delta q')(1-\delta+\delta p')}{1-\delta+\delta q'+\delta p'}$

$$v^{\pi_1}_{MDP}(1) = \frac{p'r_2 + \delta p'qr_3/(1-\delta) - c^{\pi_1}_{MDP}(1-\delta+\delta q+\delta s)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q)}. \tag{3.6}$$

We can now derive $WTP^{\pi_1}_{MDP}$ by applying Definition 3.2 and solving for $c^{\pi_1}_{MDP}$. Relative to not intervening, the policymaker is willing to pay $WTP^{\pi_1}_{MDP}$ every time the process is in State 1 in exchange for replacing the transition probability p out of State 1 with the more favorable probability p'. The expressions for the WTPs in the general and special (i.e., $s = s' = 0$) cases are provided in Table 3.2, for this policy π_1 as well as the other MDP policies. The derivations of the WTP expressions for policies π_2 and π_{12}, which are procedurally analogous, are provided in the appendix.

Note that MDP stationary policy π_k and MRP parameterization μ_k induce exactly the same underlying transition probability matrix. However, the mechanism of accounting for policy cost is fundamentally different and so $WTP^{\pi_k}_{MDP}$ and $WTP^{\mu_k}_{MRP}$ are not directly comparable policy decision thresholds.

3.4.3 Analytical results common to both the MRP and MDP models

Using the WTP results derived above, we analytically characterize key behaviors which are common to both the MRP and MDP models in this subsection, then establish their most important differences in Section 3.4.4.

In our cost-benefit approach, the magnitudes of the rewards received in States 2 and 3 are major drivers of the policymaker's WTP for policy intervention. We therefore begin with Proposition 3.1, which characterizes the effects that the state rewards have on the policymaker's WTPs for policy intervention. We first note that all WTPs for policy intervention are linear in both rewards r_2 and r_3, a direct consequence of the Bellman equations used to derive the WTP expressions. We would not expect this to be the case if, for example, the policymaker were risk-averse and were maximizing the total expected discounted *utility* of rewards. Furthermore, we find that while WTPs are always increasing in the absorbing state's reward (r_3), they are not necessarily increasing in the intermediate state's reward (r_2). Whether WTP is increasing or decreasing with respect to r_2 depends on a tradeoff between competing mechanisms, which we describe below.

Proposition 3.1. *All WTPs in both models increase linearly with r_3, but the WTPs for policy interventions targeting State 2, or States 1 and 2, can decrease linearly with r_2.*
Proof. See Appendix A.1. □

The policies targeting State 1 only, μ_1 and π_1, raise the transition probability from State 1 to State 2 (from p to p'), meaning that r_2 rewards tend to be earned sooner in less discounted periods. Hence, the WTPs for State 1 policies are increasing in the r_2 state reward. Similarly, these policy interventions mean that State 3 tends to be reached sooner, so their WTPs are also increasing in

For interested readers, a comprehensive comparative statics analysis of all WTP expressions with respect to the model parameters is included in the appendix.

r_3. However, policies targeting State 2 only (μ_2 and π_2) raise q to q', meaning that less time is spent in State 2, and therefore the State 2 reward is collected less often. Indeed, the policymaker is paying to leave State 2 faster, and the incentive to do this is weaker if the reward for being in State 2 is higher. On the other hand, in the general case, policy intervention also decreases s to s', which can make the process spend more time in State 2 by opposing regression to State 1. We find, then, that the reactions of $WTP^{\mu_2}_{MRP}$ and $WTP^{\pi_2}_{MDP}$ to a change in r_2 depend on the tradeoff between the intervention increasing q to q' but decreasing s to s'. Therefore, the behaviors of these WTPs with respect to r_2 depend on the particular parameterization. Finally, the policies that target State 2 imply reaching State 3 sooner, so their WTPs are always increasing in r_3.

For policies targeting both States 1 and 2, there exists a similar tradeoff with respect to the intermediate state reward r_2. Working to increase $WTP^{\mu_{12}}_{MRP}$, raising p to p' and decreasing s to s' imply that more time is spent collecting r_2 in State 2. Working in the opposite direction, increasing q to q' causes less time to be spent in State 2. Again, the behavior of this WTP with respect to r_2 depends on the particular parameterization.

Next, we turn to the effects of the status-quo transition probabilities – those which are improved upon via policy intervention – on the WTPs for the policies. In Proposition 3.2, we find that the WTPs in both models increase at an accelerating rate as the status-quo transition probabilities of advancing from states targeted by the policies (i.e., p for policies μ_1 and π_1, and q for

---

Establishing the behaviors of $WTP^{\pi_{12}}_{MDP}$ analytically has proven far less tractable than that of $WTP^{\mu_{12}}_{MRP}$. Nevertheless, based on numerical results, this WTP appears to share many of the features of the μ_{12} policy in the MRP model.

policies μ_2 and π_2) decrease toward zero.

Proposition 3.2. *In both models, as the status-quo transition probability of the diffusion process advancing from a stage declines toward zero, the WTP for the policy targeting this stage increases at an accelerating rate.*
Proof. See Appendix A.2. □

While it is immediately intuitive why the WTPs for State 1 policy interventions decrease with p and WTPs for State 2 policy interventions decrease with q, the second-order property of these relationships is a noteworthy consequence of the model structure considering how few assumptions are required to support it. Another way to interpret these results is that overestimating the status-quo transition probability will be more problematic for cost-benefit analysis than underestimating this parameter. While the analysis of $WTP^{\pi_{12}}_{MDP}$ is not analytically tractable, we are able to prove that $WTP^{\mu_{12}}_{MRP}$ also increases more and more steeply as the status-quo p and q transition probabilities decline towards zero.

We now shed light on the implications of the possibility of regressing from State 2 to State 1. Including the possibility of regressing enriches our model's ability to inform technology policy.

Proposition 3.3. *In both models, as the status-quo probability (s) of the regressive transition from State 2 to State 1 increases, the WTP for State 2 intervention increases, though this effect is diminishing on the margin.*
Proof. See Appendix A.3. □

Policy intervention in State 2 works to not only increase the transition probability from State 2 to State 3, but also to *decrease* the probability of regressing from State 2 to State 1. Naturally, then, increases in s, the status-quo transition probability, induce increases in WTP (Proposition 3.3). The higher the status-quo transition probability s is, the more time the process spends oscillating between State 1 and State 2, increasing the expected time to absorption. Therefore, the value of the component of State 2 policy intervention that increases the transition probability from State 2 to State 3 diminishes, since it is rendered more ineffective by the high regressive transition probability. Hence, while the WTP increases with the status-quo regressive transition probability, its increases are diminishing on the margin. This oscillation between early and intermediate stages may be interpreted as the technology succumbing to the "valley of death," in which early commercial demonstration of the technology beyond protected niches fails due to market and innovation system failures. In directly stimulating the diffusion process through, for example, public R&D money, a policymaker can prevent a slip into the valley of death (Weyant, 2011). However, allocating public funds for a technology at this stage can be controversial. For example, government failures through "technology pork barrel" spending and limitations on "picking the winner" may make policymakers hesitant about continuing to support individual technologies (Nemet et al., 2018). While it is beyond the scope of this chapter to assess specific policy formulations, our analytical results provide general insights on the relative values of supporting technology deployment at different stages.

3.4.4 Analytical results that highlight differences between the MRP and MDP models

The previous subsection analytically established several key properties that are common to both the MRP and MDP models. Here, in Proposition

3.4, we identify the most striking difference between the two models, which carries significant policy implications.

Proposition 3.4. *With respect to the effectiveness of policy intervention (i.e., how much it improves the transition probabilities), the WTPs exhibit diminishing returns in the MRP but constant returns in the MDP.*

Proof. See Appendix A.4. □

For State 1 policy interventions, $WTP^{\mu_1}_{MRP}$ exhibits diminishing returns with respect to raising the policy-enhanced transition probability p', whereas $WTP^{\pi_1}_{MDP}$ exhibits constant returns. We attribute this contrast to the different cost accounting mechanisms. The total cost of stationary policy π_1 is directly related to the time spent in State 1, which is not the case for μ_1 in the MRP model. Therefore, beyond the benefits of reaching states with rewards r_2 and r_3 faster, replacing p with the higher probability p' in the MDP model has the additional benefit of pushing the process out of State 1 and thus avoiding more periods incurring the policy cost $c^{\pi_1}_{MDP}$. This additional motivation to move out of State 1 in the MDP is not present in the MRP case. As a general technology policy insight, we believe that the added importance of moving the diffusion process along when a lack of progress would imply recurring policy costs is important to recognize.

For policies targeting State 2, increases in q' and decreases in s' also generate constant returns in the MDP model, but diminishing returns in the MRP model. The logic is analogous to the above discussion about policies targeting State 1, and once again marks a major difference between policy interventions in the MRP and MDP frameworks.

Again, while we are able to analytically prove that $WTP^{\mu_{12}}_{MRP}$ for the MRP policy targeting both States 1 and 2 exhibits diminishing returns with respect to p' and q', establishing a similar result for $WTP_{MDP}^{\pi_{12}}$ is analytically intractable. Furthermore, in order for our WTP approach to make sense for the MDP model (as structured by Definition 3.2), the policy costs incurred in States 1 and 2 need to be equal. This restrictive assumption may not be very realistic. So, to gain some insight into policy π_{12} that targets States 1 and 2 simultaneously in the MDP, in Section 3.5 we compute numerical results for the most general MDP model in which policy costs in States 1 and 2 can differ.

We elaborate on other key differences between the MRP and MDP models in Propositions 3.5 and 3.6, which explore the implications of the possibility that the diffusion process regresses. First, in Proposition 3.5, we find that, while the WTP for policy intervention in State 1 decreases monotonically with the regressive transition probability in the MDP model, the effect on the WTP is non-monotonic in the MRP model.

Proposition 3.5. *Increasing the probability of the regressive transition (s) decreases the WTP for State 1 intervention monotonically in the MDP, but its effect on the WTP for State 1 intervention is non-monotonic in the MRP.*

Proof. See Appendix A.5. □

In the MRP model, until s reaches some constant C_2, incremental increases in s raise the policymaker's WTP for policy intervention targeting State 1. So, in this region of s, a higher s implies a more urgent need to push the technology transition out of State 1. However, beyond this constant C_2, $WTP_{MRP}^{\mu_1}$ actually declines in s. The fact that the WTP does not increase with s over the entire allowable domain of s is actually straightforward to interpret. Indeed, as s gets very close to one, the policy intervention targeting

---

C_2 may lie outside $(0, 1-q)$, the allowable domain of s.

State 1 becomes ineffective; even when the technology diffusion process reaches State 2, it would be far more likely to regress to State 1 than to advance to State 3 and complete the transition. There is thus limited value in increasing the transition probability out of State 1 to p' if s is very high.

However, in the MDP model, $WTP^{\pi_1}_{MDP}$ is monotonically decreasing everywhere with respect to the regressive transition probability s, which was not the case in the MRP model. The contrast is fairly intuitive. A higher value of s means that the diffusion process is more likely to return to, and spend more overall time in, State 1. In the MDP model, spending more time in State 1 means incurring the policy cost $c^{\pi_1}_{MDP}$ more often, thus making policy π_1 less attractive. Hence, this contrast is due to the different cost accounting mechanisms. A policymaker, then, would need to pay careful attention to the probability of regressing if she is considering policy intervention that targets State 1 via an up-front policy cost. If this probability of regressing is particularly high, policy intervention targeting State 2's regressive transition probability may be more effective in supporting the technology transition.

In Proposition 3.5 above, we found that the effect the regressive transition probability has on the WTP for State 1 policy intervention is non-monotonic in the MRP model. This non-monotonic behavior is, in fact, unique to the MRP model, as presented in Proposition 3.6.

Proposition 3.6. *Including the regressive transition induces a non-monotonic relationship between the WTP and the non-targeted, status-quo transition probabilities in the MRP model only.*
Proof. See Appendix A.6. □

We begin with policies targeting State 1. The μ_1 policy intervention only increases the transition probability from the initial to the intermediate diffusion stage (p'), but is made more valuable by a higher transition probability from intermediate to complete diffusion (q). With no danger of regressing from State 2 back to State 1, a higher q always implies a greater WTP. The interpretation is not immediately intuitive; no matter how high q becomes, incremental increases in q always add value to μ_1, though diminishing on the margin. However, if there is a danger of regressing from State 2 back to State 1 (i.e., $s > 0$), then there may exist a $C_1 \in (0, 1-s)$ such that $WTP^{\mu_1}_{MRP}$ reaches a maximum at $q = C_1$, then falls thereafter. In other words, there may exist a point at which further increases in q actually reduce the benefit of policy intervention in State 1, since q is already quite high and the technology transition could possibly regress repeatedly from State 2 back to State 1. In the MDP model, however, WTP is *always* increasing with respect to q and always decreasing with respect to s. Again, as described under Proposition 3.5, we attribute this to the different cost accounting mechanisms.

For policies targeting State 2 in the MRP model, we also find non-monotonic behavior if there is a possibility of regressing. If there is no danger of regressing from State 2 back to State 1 (i.e., $s = 0$), then the policymaker is willing to pay more for State 2 policy intervention as p increases. A higher p implies that the process transitions faster from the initial to the intermediate diffusion stage, which is targeted by μ_2. Therefore, the full technology diffusion process will be completed faster, and policy intervention in State 2 to accelerate the final transition to State 3 becomes more valuable because it now tends to occur in less discounted time periods. However, this need not be the case if there is

---

C_1 may lie right of $(0, 1-s)$, in which case the general and special cases have identical first-order behavior in q.

a danger of regressing back to State 1 (i.e., $s, s' > 0$). In particular, it may be the case that when $p > C_3$, a value where $WTP^{\mu_2}_{MRP}$ reaches a maximum, further increases in p actually reduce the value of policy intervention μ_2 to raise the probability of advancing from the subsequent, intermediate stage. In other words, if there is a danger of regressing from State 2 back to State 1 and p is high enough, then the later-stage policy intervention μ_2 could lose some of its benefit.

In the MDP model, however, there is no non-monotonic behavior. Instead, a tradeoff captures how the WTP behaves with the transition probability p. Under stationary policy π_2, the policy cost is incurred whenever the diffusion process is in State 2. If there is no possibility of regressing from State 2 back to State 1, then once the process transitions to State 2, the total cost of the policy no longer depends on p. However, in the general case, there are two possibilities. $WTP^{\pi_2}_{MDP}$ is either concave increasing or convex decreasing in p; which tendency prevails depends on a tradeoff. If the difference $s' - s$ is relatively large, then policy π_2 significantly reduces the probability of regressing. In this case, as p increases, $WTP^{\pi_2}_{MDP}$ decreases because the consequences of regressing to State 1 – which the policy helps avoid – are less dire. With a higher p, the process is less likely to remain in State 1 for long. On the other hand, if the difference $q' - q$ is relatively large, then increases in p make π_2 more valuable by driving the process toward the affected State 2 faster. Therefore, the policy tends to act in less discounted time periods, and $WTP^{\pi_2}_{MDP}$ increases with p. So, the behavior of the WTP with respect to p depends on whether π_2 has a greater effect on raising q or reducing s. This

The inequality that represents this tradeoff can be found in Appendix A.6.

important tradeoff appeared in our analysis of the possible non-monotonicity of $WTP^{\mu_2}_{MRP}$ in p.

3.5 Numerical examples

In this section, we fully parameterize the most general MDP model, including the policy costs, and solve the MDP numerically to explore how the optimal technology policy portfolio varies over the parameter space. Instead of analyzing the WTP thresholds, as we did in the previous section, here we determine which policy portfolio maximizes the total expected discounted reward for each parameter setting. The policymaker has two technology policy interventions available. One intervention targets State 1, the other targets State 2, and their costs (c^1_{MDP} and c^2_{MDP}, respectively) need not be equal. The decision alternatives for the policymaker are then the four possible policy portfolios, each of which is a stationary policy for the MDP: do not intervene and settle for the status quo (π_0), implement only the intervention targeting State 1 (π_1), implement only the intervention targeting State 2 (π_2), or implement both interventions simultaneously (π_{12}). We compute the optimal policies numerically via policy iteration. The figures we present and discuss below, which we call optimal policy mappings, illustrate how our model can be used to guide technology policy decision making in the most general context.

We begin with Figure 3.3, which shows how the optimal policy varies with the status quo transition probabilities p and q. Figure 3.3(a) on the

---

The policy iteration algorithm for solving MDPs iterates over policies, monotonically improving the value functions, which leads to guaranteed convergence if there are finite numbers of states and actions Bertsekas (2012). The WTP quantities derived in Section 3.4 are relative measurements, so to find the strictly best policy, we employ the policy iteration algorithm.

left represents the general case where the regressive transition from State 2 back to State 1 is possible, and Figure 3.3(b) on the right corresponds to the special case where this transition is ruled out. The color at a given (p, q) location indicates which technology policy portfolio is optimal for that parameterization. If both p and q are low, it is optimal for the policymaker to intervene in both states. If p is low but q is high, the policymaker should choose to implement the State 1 intervention only, since intervention in State 2 is no longer warranted. Comparing the left and right plots, though, when $s > 0$ in the general case, the policymaker requires a higher value of q to forgo policy intervention in State 2. Next, when p and q are both high, the policymaker should take no actions. The region where it is optimal to not intervene is smaller in the general case on the left than in the special case on the right. Indeed, the possibility of regressing from State 2 back to State 1 is an additional motivation to raise the probabilities of advancing through the diffusion process, especially from State 2 where the regressive transition originates. We draw from this an important conclusion: when the regressive transition from State 2 back to State 1 is allowed, the State 2 Only and States 1 and 2 regions are larger, whereas the State 1 Only and No Intervention regions are smaller.

Figure 3.4 is an optimal policy mapping with the same format as Figure 3.3, but here the policymaker locates a position with respect to the status-quo transition probability from State 1 to State 2 (p) and the cost of policy intervention in State 1 (c^1_{MDP}). Clearly, it is never optimal to pay any amount to intervene in State 1 if the policy-induced transition probability p' is less than p, the region to the right of the vertical dashed line in the figure. Furthermore, as the policy cost increases, the domain of p over which it is optimal for the

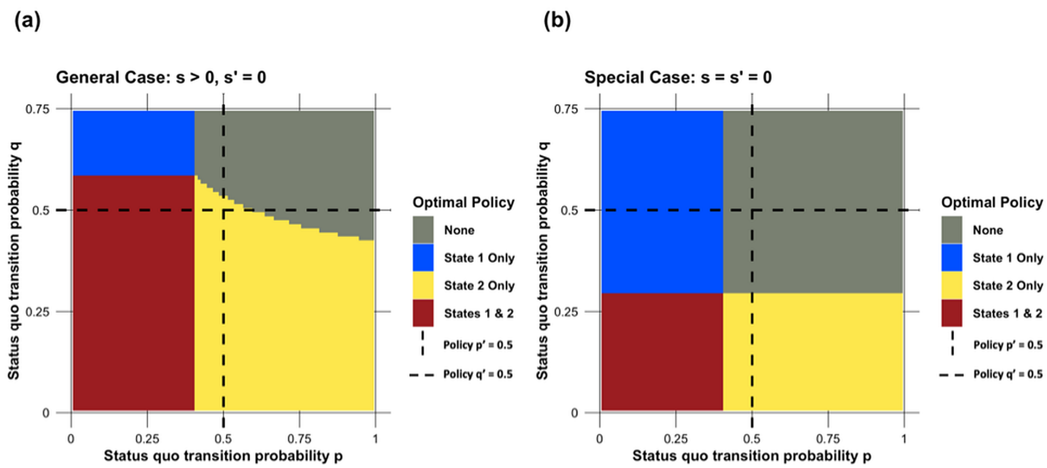

Figure 3.3. Optimal policy mapping with respect to the status quo transition probabilities p and q. The plot on the left (a) is the general case with $s > 0$ and the plot on the right (b) is the special case with $s = 0$. The baseline parameterization is $p' = 0.5$, $q' = 0.5$, $s = 0.2$, $s' = 0$, $c^1_{MDP} = 20$, $c^2_{MDP} = 30$, $r_2 = 50$, $r_3 = 100$, and $\delta = 0.95$. The dashed lines represent the policy-enhanced transition probabilities p' and q'. Because s is fixed at 0.2 for this sensitivity analysis, q on the y-axes cannot exceed 0.8, lest the transition probability matrix be ill-defined. Therefore, we have depicted an upper bound on q of 0.75 so that the probability of remaining in State 2 $(1 - q - s)$ is never 0.

.

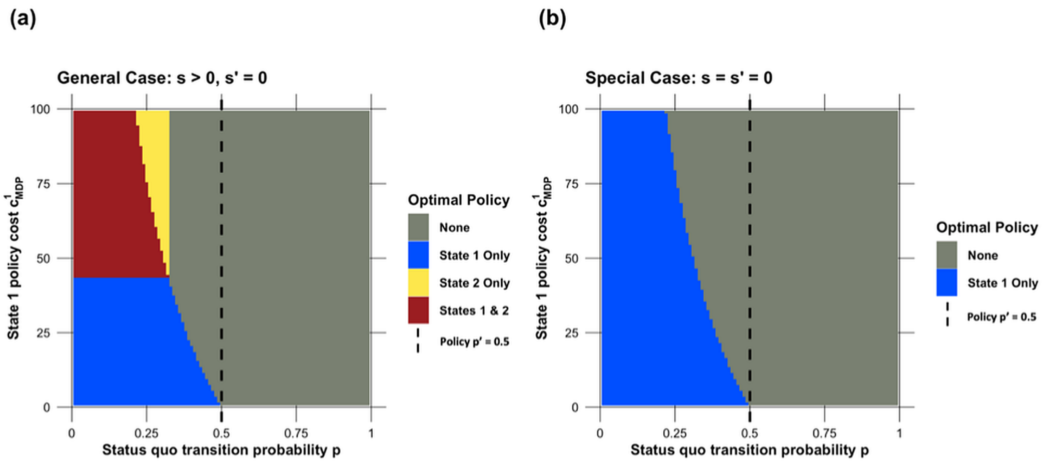

Figure 3.4. Optimal policy mapping with respect to the status quo transition probability p and the recurring cost of State 1 policy intervention c^1_{MDP}. The plot on the left (a) is the general case with $s > 0$ and the plot on the right (b) is the special case with $s = 0$. The baseline parameterization is $p' = 0.5$, $q = 0.25$, $q' = 0.35$, $s = 0.1$, $s' = 0$, $c^2_{MDP} = 50$, $r_2 = 50$, $r_3 = 100$, and $\delta = 0.95$. The dashed line represents the policy-enhanced transition probability p'.

policymaker to intervene shrinks. In the special case with $s = 0$, the only policies which are ever optimal are the laissez-faire approach and intervening in State 1 only. In the general case with $s > 0$, however, when p is low and c^1_{MDP} is high, it can be optimal for the policymaker to intervene in both States 1 and 2 or even to target State 2 only. Intuitively, when the cost of policy intervention in State 1 is high enough, it is valuable to reduce s from State 2 so that this high cost is incurred less often. In other words, an expensive policy that targets State 1 should be complemented by an intervention in State 2 to help prevent the recurrence of high policy costs from spending a lot of time in State 1. Again, we see that the possibility of the diffusion process regressing significantly alters the optimal policy landscape.

Figure 3.5 presents a similar optimal policy mapping with respect to the status-quo transition probability and policy cost, but for State 2 instead of State 1. When q and c^2_{MDP} are both small, it is optimal to intervene in both States 1 and 2. With a higher cost, it is no longer optimal to select the policy portfolio that targets both states. It is very interesting that, as the State 2 policy intervention becomes more expensive, it is often the State 1 intervention that is abandoned rather than the State 2 intervention. Under this particular parameterization, obtaining more favorable transition probabilities from State 2 appears to be inherently more valuable. Another striking feature of Figure 3.5 are the different optimal policies to the right of the vertical dashed lines ($q' = 0.5$) in the general case with $s > 0$ on the left and the special case with $s = 0$ on the right. In the special case, there is no reason to pay any amount to replace q with a lower q', so it is optimal to intervene in State 1 only. However, in the general case, under some circumstances, it is actually optimal for the policymaker to reduce q if it comes with a lower s. Essentially, the policymaker improves her prospects by accepting a lower probability of advancing from State 2 to State 3 in exchange for a lower probability of regressing from State 2 back to State 1. This unintuitive behavior begins to disappear as c^2_{MDP} increases and the option of not intervening takes over. As before, a consistent theme we observe in the results is that the possibility of regressing from a more advanced stage to an earlier one critically alters the diffusion process and the optimal policy approach.

3.6 Case study: Lithium-ion batteries

While our models are quite abstract to permit analytical results, the model primitives (states, transition probabilities, policy intervention costs, and state rewards) can be interpreted and parameterized to inform technology policy

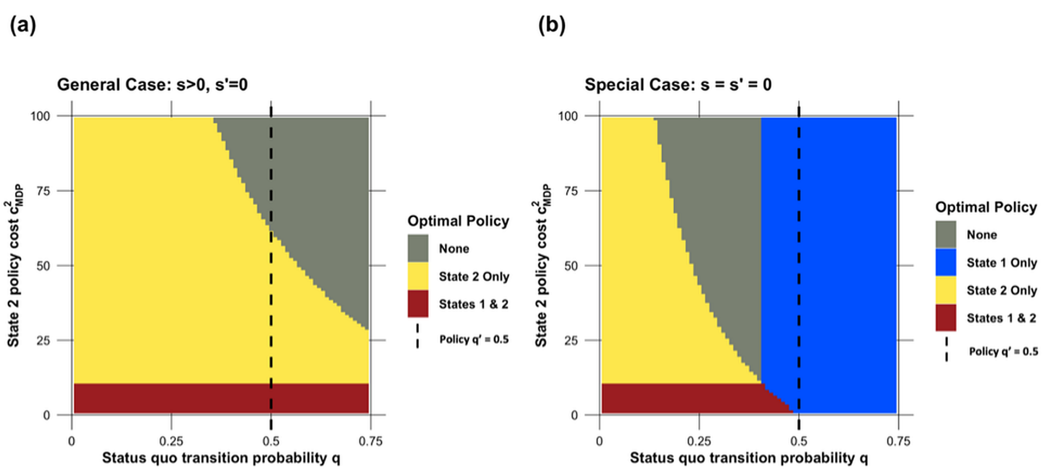

Figure 3.5. Optimal policy mapping with respect to the status quo transition probability q and the recurring cost of State 2 policy intervention c^2_{MDP}. The plot on the left (a) is the general case with $s > 0$ and the plot on the right (b) is the special case with $s = 0$. The baseline parameterization is $p = 0.1$, $p' = 0.2$, $q' = 0.5$, $s = 0.1$, $s' = 0$, $c^1_{MDP} = 65$, $r_2 = 50$, $r_3 = 100$, and $\delta = 0.95$. The dashed line represents the policy-enhanced transition probability q'.

in reality. In this section, we demonstrate the practical applicability of our approach by conducting a case study on technology policy for lithium-ion (Li-ion) batteries for electric vehicles (EVs) using the MDP model. Note that this case study demonstrates the application of the MDP model to a technology development process, rather than diffusion.

The timely decarbonization of the transport sector is one of the most challenging components of climate change mitigation, as the current performance and cost characteristics of batteries mean that EVs are struggling to displace their gasoline-fueled counterparts. Several expert elicitation studies have attempted to quantify the uncertainties in Li-ion battery development by surveying numerous experts in the field (Few et al., 2018; Verdolini et al., 2018). While each expert elicitation follows its own methodology, scenario definitions, and outcome metrics, the results of these studies can serve as useful inputs to stochastic decision making frameworks like our Markov models. As it is outside the scope of this study to conduct our own expert elicitation designed specifically to parameterize our models, we adapt the expert elicitation results from Baker et al. (2010) to fit our parameter definitions. The Baker et al. (2010) study provides experts' subjective assessments of the probabilities of successfully achieving two well-defined technological endpoints, conditional on two public R&D funding scenarios for Li-ion batteries. To demonstrate the application of our MDP model to the Li-ion battery case, we parameterize it using the probability assessments of one of the experts surveyed in that study, shown in Table 3.3.

	Public R&D funding scenario	
	\$30M/yr over 10 years	\$70M/yr over 10 years
Probability of achieving Low Endpoint	0.2105	0.3209
Probability of achieving High Endpoint	0.0656	0.1503

Table 3.3. Expert 5's subjective probability assessment on Li-ion battery technology from Baker et al. (2010).

3.6.1 Case study parameterization

We let States 2 and 3 in our MDP represent the Low and High Endpoints, respectively, from Baker et al. (2010). In their paper, each endpoint is defined according to capital cost, power density, specific energy, lifetime, and recharge rate benchmarks. State 1 represents the current state of Li-ion technology at a capital cost of \$384/kWh, the baseline figure for 2010 referenced by Baker et al. (2010). Even the Low Endpoint represents significant technological improvements relative to the characteristics at the time of publication of the elicitation study. To translate the subjective probability assessments into transition probabilities between states in our MDP model, we assume that (1) transitions occur in five-year intervals, (2) there is no possibility of the development process regressing from State 2 to State 1 (i.e., the special case $s = s' = 0$), and (3) the development process with no policy intervention

---

Baker et al. (2010) defined these endpoints through discussions with experts. The Low Endpoint's characteristics are: specific energy of 150 Wh/kg, power density of 460 W/L, lifetime of 8 years, recharge rate of 6 hours, and capital cost of \$200/kWh. The High Endpoint's characteristics are: specific energy of 200 Wh/kg, power density of 600 W/L, lifetime of 10 years, recharge rate of 3 hours, and capital cost of \$125/kWh.

Our case study thus corresponds to a policymaker in 2010 making technology policy decisions on Li-ion batteries based on the state of the technology and information available in that year. While we would have preferred to present a more forward-looking case study, more recent expert elicitation results in the form required by our models could not be identified. As a demonstration of applying our model using expert elicitation results as inputs, our case study suffices.

(status-quo transition probabilities p and q) models the development of Li-ion EV batteries under the lower \$30M/yr funding scenario. Therefore, the recurring cost of policy intervention in both States 1 and 2 is \$200M, which represents the \$40M/yr incremental cost of the more aggressive R&D funding scenario maintained over a five-year period duration. To determine the p and q transition probabilities, we equate the total probability of reaching State 2 in two periods (10 years) to 0.2105, the expert's probability assessment of reaching the Low Endpoint in 10 years under the baseline funding trajectory. Next we equate the total probability of reaching State 3 in two periods (10 years) to 0.0656, the expert's probability assessment of reaching the High Endpoint in 10 years under the baseline funding trajectory. We determine the p' and q' transition probabilities the same way, except we use the probability assessments under the higher (\$70M/yr) funding trajectory. We solve the system of equations

$$\begin{cases} 0.2105 = (1-p)p + p(1-q), \\ 0.0656 = pq, \\ 0.3209 = (1-p')p' + p'(1-q'), \\ 0.1503 = p'q' \end{cases} \tag{3.7}$$

by substitution to determine all transition probabilities p, p', q, and q'.

Finally, we parameterize the state rewards r_2 and r_3 based on the five-year total cost savings on Li-ion EV battery capacity deployment in the U.S. resulting from being at the Low (\$200/kWh) or High (\$125/kWh) Endpoint, respectively, compared to the baseline capital cost (\$384/kWh). For example,

In theory, we could choose any (smaller) interval length for transitions, but five-year intervals were chosen because they yield a relatively simple quadratic system of equations to solve for the transition probabilities.

Table 3.4. Complete parameterization of the MDP model for the Li-ion battery case study, based on Expert 5's probability assessments from Baker et al. (2010).

Parameter	Value
p	0.1492
p'	0.2728
q	0.4397
q'	0.5509
$c_{MDP}^{\pi_1}$	\$200M
$c_{MDP}^{\pi_2}$	\$200M
r_2	\$17,112M
r_3	\$24,087M
δ	0.95

assuming an average annual U.S. deployment of 0.62M EVs per five-year interval (IEA, 2019) and an average battery capacity of 30 kWh, the reward in State 2 is $r_2 = (\$384/\text{kWh} - \$200/\text{kWh}) * 30\ \text{kWh} * 0.62\text{M} * 5\ \text{yrs} = \$17,112\text{M}$. This accounting is in line with our model's objective: to determine if and when additional public R&D funding is warranted. In other words, the model assesses whether the expected cost savings from deliberate investments to accelerate the development of Li-ion EV batteries outweigh the costs of these policy interventions. Finally, we choose a standard discount factor of 0.95. The complete parameterization of the MDP model is given in Table 3.4.

3.6.2 Case study results

Based on the parameterization in Table 3.4, we calculate the expected total discounted rewards for the four possible technology policies in Table 3.5. The optimal policy, therefore, is to fund public R&D for Li-ion batteries at the higher \$70M/yr rate until the High Endpoint (State 3) is achieved.

Table 3.5. Expected total discounted rewards for the four possible policies in the Li-ion battery case study. It is optimal for the policymaker to fund R&D at $70M/yr in both States 1 and 2.

		State 2	
	Funding level	**$30M/yr**	**$70M/yr**
State 1	**$30M/yr**	$363,255M	$365,136M
	$70M/yr	$411,277M	**$413,409M**

Table 3.5 reveals that the net benefits of increasing early public R&D funding (State 1) for Li-ion batteries are particularly large, and that the net benefits of later R&D funding (State 2) are less pronounced (though still positive). Furthermore, we have arrived at the optimality of high levels of R&D funding using a conservative parameterization of the state rewards, making our case study's conclusions rather persuasive. First, we only consider the application of Li-ion batteries to EVs. In reality, improvements in Li-ion batteries would spill over to other applications, such as grid-scale electricity storage to balance intermittent renewable generation, increasing benefits at no additional cost. Second, we only consider EV battery deployment in the U.S. Improvements driven by U.S. R&D spending would likely generate benefits in other countries as well. Third, our case study assumes a fixed annual deployment of Li-ion batteries in EVs. Reducing battery costs would stimulate more extensive adoption of the technology, thus raising benefits. Fourth, our crude estimation of benefits only considers direct capital cost savings due to cheaper batteries in EVs. The monetized environmental benefits of reduced air pollution and greenhouse gas emissions are not counted in our rewards.

3.6.3 Future case studies

Our case study has demonstrated how the results of expert elicitation studies can be used to parameterize the inputs to our Markov models. However, some limitations arose due to the fact that we had to adapt the results of an existing expert elicitation study to the specific structure of our MDP model. To address these shortcomings, a future elicitation could be carried out that clearly defines the relevant attributes of the technology in each of the states, and designs the study to directly elicit the transition probabilities conditional on policy decision alternatives. Questions necessary to elicit the reward values could be included within the expert elicitation, or the rewards could be estimated separately through the type of calculation we performed above, or through the use of a more sophisticated model (e.g., an energy-economy model that maps technology characteristics to minimized total cost objective values). Most generally, our case study suggests that expert elicitations will be most useful for informing policy when they are structured in harmony with a decision making model that can directly incorporate their results as inputs.

3.7 Conclusions

In this chapter, we have developed and analyzed two Markov models of technology transitions to obtain generalizable insights into technology policy decision making under uncertainty. We emphasize that our framework is a cost-benefit analysis approach, instead of, for example, a cost-effectiveness approach in which the policymaker faces a fixed policy budget. The first model was a Markov reward process (MRP) that represents policy interventions with one-time, upfront costs, while the second model was a Markov decision process (MDP) that describes policy interventions with recurring costs. We derived analytical expressions for the willingness to pay (WTP) for policy interventions that improve the probabilities of the technology diffusion or development process advancing at various stages. We then analytically established key similarities and differences between the two models. Next, we numerically solved the most general MDP model to explore how the optimal technology policy portfolio varies over the input parameter space. Finally, we applied the MDP model to a case study on lithium-ion (Li-ion) batteries for electric vehicles (EVs).

We view the models themselves as our most significant contributions to the literature. They constitute a theoretical framework for analyzing technology policy decision making under uncertainty that complements previous case studies, empirical data analyses, qualitative models, and domain-specific studies. To the best of our knowledge, we are the first authors to analytically investigate technology policy decision making using an MDP methodology. Despite our theoretical bent, the case study serves to demonstrate that our models can be parameterized to provide practical decision support to policymakers. We believe that technology policy formulation is a very important topic that can benefit a great deal from the continued application of operations research tools.

Limiting assumptions are inevitable in this type of theoretical modeling exercise designed to yield analytical results. The Markov assumption could be limiting if the complete history of technology policy support influences the current transition probabilities. The stationary transition probabilities assumed in our models cannot accommodate probabilities that are affected by the passage of time in addition to the state and policy action. Our state rewards are also assumed to be exogenous and known, while remaining constant over time, limiting their ability to reflect changes in market size. Indeed, beyond uncertainty in the diffusion or development process of a technology, future research could consider modeling uncertainty in the model's primitives including the policy costs, state rewards, and the transition probabilities themselves. Furthermore, we have assumed that our policymaker is risk-neutral. Combining such uncertainty with a policymaker's risk attitude may generate valuable insights and lead to a stronger decision tool for informing real-world technology policy. Nevertheless, our results all permit intuitive explanations, as described throughout the chapter. The WTP thresholds were derived by treating technology policy as a cost-benefit problem, so their usefulness as decision guides would not necessarily extend to cost-effectiveness settings where a fixed total budget for policy interventions is defined ex ante. In that case, not every policy that generates net benefits could be pursued simultaneously, so only the interventions with the greatest benefits relative to costs should be implemented. Furthermore, our cost-benefit approach to technology policy decision making omits other factors confounding policy design such as political pressures and macroeconomic and geopolitical trends.

In terms of the specific results we obtain, the MRP and MDP models demonstrate some intuitive similarities. WTPs vary linearly with the rewards. They always increase with respect to the reward for being in the complete diffusion stage, but the WTP for policy intervention in the intermediate stage can decrease with the reward obtained in this stage since this reward makes completing the diffusion process less urgent. As the status-quo probability of the diffusion process advancing from a stage declines toward zero, the WTP for policy targeting this stage increases more and more steeply.

The possibility of regressing from the intermediate stage back to the initial stage has a substantial impact on the behaviors of both models, and carries important policy implications. In general, this possibility makes policy intervention less valuable in the initial stage but more valuable in the intermediate stage. With a danger of regressing from the intermediate stage back to the initial stage, the policymaker has a higher WTP to raise the probability that the diffusion process will advance from the intermediate stage to the complete diffusion stage. The numerical results reveal that the presence of the regressive transition in the MDP model makes policy intervention in the intermediate stage an important complement to earlier intervention in the initial stage. Without the former, the latter could incur policy costs repeatedly as the process makes it to the intermediate stage only to return to where it began. In fact, under certain circumstances, the policymaker would even be willing to pay for an intervention that actually reduces the probability of advancing from the intermediate stage to the complete diffusion stage if it comes with a sufficiently large reduction in the probability of regressing back to the initial stage. The possibility of regressing is also a necessary condition for all of the non-monotonic behaviors we uncovered.

The structural properties of the MRP and MDP models exhibit a few notable differences that suggest how policymakers ought to think differently about technology policy interventions with one-time versus recurring costs. The most striking difference is that, as the enhanced transition probabilities that intervention would purchase improve further, the resulting increases in WTP are subject to diminishing returns in the MRP, but are subject to constant returns in the MDP. The added value of incremental increases in the probabilities of advancing do not diminish in the MDP because the desire to avoid incurring policy costs repeatedly is an additional motivation to move the diffusion process forward. The same reasoning explains why the MDP is more powerfully affected by the possibility of a regressive transition than the MRP is.

Despite the abstract nature of our models, which provide a valuable theoretical framework for analyzing technology policy decision making under uncertainty, they can be applied to real technology problems as demonstrated by our case study on Li-ion batteries. However, the case study highlighted how expert elicitations and decision making models really ought to have harmonized structures (with the expert elicitation results directly incorporated into a decision making model as inputs) in order to more usefully inform policy. Moving forward, we hope that other operations researchers will be attracted to the technology policy topic, as it has substantial relevance to some of society's grandest challenges.

3.8 Acknowledgments and notes

Benjamin Leibowicz contributed to the conceptualization of the topic. A version of this chapter has been published in *European Journal of Operational Research* (Brozynski and Leibowicz, in press), and we acknowledge the excellent comments and suggestions from three anonymous reviewers. We also thank John Hasenbein and seminar audiences at the University of Texas at Austin and INFORMS Annual Meeting 2018 for helpful comments and suggestions.

Chapter 4

A bilevel optimization model of infrastructure-dependent technology adoption: Overcoming the chicken-and-egg problem

4.1 Introduction

Many technologies in sectors such as energy, transportation, and telecommunications require large infrastructure systems to deliver benefits to adopters and to society at large (Hughes, 1987). Some emerging *infrastructure-dependent technologies* promise substantial social benefits, and policymakers are thus interested in allocating public funds to support their diffusion. Relevant examples today include 5G-enabled telecommunication devices and battery electric vehicles (BEVs). The 5G wireless revolution, with its faster speed and lower latency than previous technologies, promises novel applications such as remote surgery and coordinated autonomous vehicle fleets (Cheng, 2019). However, 5G-enabled end-user devices remain more expensive than previous generation 4G alternatives, and the deployment of 5G radio hardware by U.S. carriers is limited to a select few urban areas. Similarly, BEVs promise to decarbonize transportation while achieving superior performance with lower maintenance costs than vehicles fueled by gasoline (Higgins et al., 2017). However, BEVs remain more expensive than their gasoline counterparts and suffer from a dearth of high-voltage and ubiquitous charging points necessary for mass adoption.

A major obstacle facing the diffusion of infrastructure-dependent technologies is the "chicken-and-egg" problem (Huétink et al., 2010; van Bree et al., 2010). On the one hand, consumers are reluctant to adopt a new technology when the infrastructure required to support it is insufficiently developed. At the same time, firms are hesitant to invest in the required infrastructure – which is typically capital-intensive and high-risk – when there are too few current adopters to make infrastructure provision profitable. The chicken-and-egg problem is one example of the coordination failures that are invoked as a justification for government policy intervention to support innovation and diffusion (Salmenkaita and Salo, 2002). It is often accompanied by additional justifications such as the positive externalities stemming from network economies of scale (Arthur, 1989) and learning-by-doing (van Benthem et al., 2008), or the desire for a technology transition to avoid the negative externalities associated with incumbent technological systems (e.g., carbon emissions) (Butter and den Hofkes, 2006; Nemet and Kammen, 2007).

Absent appropriate policy intervention, the chicken-and-egg problem can result in existing technological systems remaining locked-in despite the emergence of more appealing alternatives (Geels, 2002; Unruh, 2000). Policymakers often attempt to overcome the chicken-and-egg problem (as well as other market failures) by subsidizing both infrastructure investment and consumer purchases of the new technology. Unfortunately, the existing literature provides little guidance and few decision support tools for policymakers to determine how to optimally allocate public resources toward incentives for infrastructure investment versus consumer purchases. For example, the U.S. federal government has spent billions of dollars on tax incentives to promote the diffusion of alternative fuel vehicles and their associated refueling and charging stations.

From 2009–2013, it spent 16 times as much on vehicle purchase subsidies as it did on infrastructure investment subsidies (Leibowicz, 2018a). It is difficult to assess whether that was the most beneficial use of public funds for innovation diffusion, and the existing literature offers few insights on this important public sector problem. While some previous studies have analyzed the chicken-and-egg problem and its policy implications, they tend to be either empirical studies focusing on a particular historical case study, or structural models that are constructed to examine a specific technology and omit key decision variables and interactions. This is the research gap that we address in this chapter.

To this end, we formulate a stylized model of technology policy decision making from the perspective of a policymaker who seeks to stimulate the market penetration of an infrastructure-dependent technology. Our model is a bilevel optimization problem in which a policymaker (leader) maximizes net social benefits by setting the levels of two incentives: a subsidy for a profit-maximizing firm (follower) to invest in infrastructure that raises the benefit of adoption to consumers, and a direct subsidy for consumers to adopt the technology. Consumer uptake is then a function of the firm's infrastructure provision and the direct subsidy for consumer purchases. The policymaker's objective consists of benefits which scale with the level of adoption, minus the costs of the policy incentives themselves.

We analytically derive the firm's optimal infrastructure investment response to the upper-level policy decisions, and show that the bilevel model is equivalent to a quadratic program. To bypass non-convexity, we develop a custom solution strategy based on decomposition, and find that it performs better than directly applying an off-the-shelf solver to the potentially non-convex problem. Finally, we present a case study on the diffusion of BEVs and obtain insights into how a policymaker should optimally allocate resources to charging infrastructure and vehicle incentives.

The rest of this chapter is organized as follows. In Section 4.2, we review the most relevant literature on technology diffusion, infrastructure-dependent technologies, and the chicken-and-egg problem. We formulate our bilevel model in Section 4.3 and derive analytical insights in Section 4.4. To demonstrate the ability of our model to inform real-world technology policy, we apply it to a case study of BEVs in Section 4.5. To conclude, we summarize our main contributions and identify future research directions in Section 4.6.

4.2 Literature review

The relevant literature on technology transitions is vast, spanning qualitative and quantitative methods as well as numerous empirical case studies. In order to firmly ground our modeling approach in the literature and establish its novelty, we organize this literature review into four subsections. Section 4.2.1 provides fundamental background on technology transitions and the role of policy support. In Section 4.2.2, we review empirical case studies of infrastructure-dependent technology diffusion. Section 4.2.3 discusses notable analytical models of these processes. Section 4.2.4 reviews game-theoretic models of infrastructure-dependent technology transitions, and comments on unanswered research questions as well as the similarities and differences between our approach and existing models.

4.2.1 Technology transitions and policy support

The 5G wireless and BEV technologies mentioned in Section 4.1 are examples of potential *technology transitions*, which Geels (2002) defines as "major technological transformations in the way societal functions ... are fulfilled." A technology transition is the outcome of complex processes of technological competition and diffusion, which are subjects of a rich and interdisciplinary literature that had its origins in the mid-twentieth century but has recently become popular again due to its obvious relevance to climate change mitigation.

In the economics literature, Schumpeter (1939) theorized that innovations are combinations developed within an economy and built on the existing stock of knowledge, leading to "creative destruction" in which markets reorient and redesign themselves during the relentless process of disruptive innovation. Early technology diffusion research consisted mostly of empirical case studies published in the sociology literature. In their influential study, Ryan and Gross (1943) investigated the diffusion of hybrid seed corn and found that neighbors' experience with the innovation was the most common motivation for adoption, and that the cumulative distribution of adoption timing followed an S-curve. Coleman et al. (1957) studied the diffusion of a new drug among physicians, finding that social networks among physicians played a large role in a physician's decision to prescribe the drug early in the adoption process. These seminal works helped inspire innovation diffusion concepts and terms such as logistic S-curves, "innovator adopters," increasing returns, positive reinforcement, and network effects that remain in use today. Efforts to synthesize early empirical research and develop an analytical framework for diffusion processes culminated in Everett Rogers's seminal book *Diffusion of Innovations*, in which he conceptualized technology diffusion as a complex process that plays out gradually across communities of heterogeneous, interacting agents (Rogers, 1962).

In the operations research literature, the Bass Model (Bass, 1969) represented the diffusion process of a technology for which the rate of adoption among agents who have not yet adopted is a linear function of the number of previous adopters. Its formulation reflects the distinction between *innovator adopters* who are self-motivated to choose a new technology, and *immitator adopters* who are encouraged to adopt by their observations of others who have already done so. Bass showed that his model fit the observed diffusion processes of many consumer durables, and a number of extensions to the Bass Model have since been proposed (Jiang and Jain, 2012; Niu, 2006; Norton and Bass, 1987). Later, Arthur et al. (1987) modeled technological competition as a nonlinear (stochastic) Polya process, whereby the probability of adoption is an arbitrary function of the number of previous adopters. Arthur (1989) modeled the diffusion process of a technology by a sequence of adoption decisions made by two types of agents. This research showed that under increasing returns (i.e., benefits increase in the number of previous adopters), technological outcomes cannot be predicted ex-ante and an economically efficient market outcome cannot be guaranteed. The evolution of the market is non-ergodic in that small chance events tip the allocation toward one dominated by a single technology, instead of being averaged away. Furthermore, there is a risk of becoming locked-in to a technology pathway with inferior long-run benefits if there is an early streak of agents who prefer an initially appealing but slow-to-improve technology.

These concepts of path-dependence and lock-in have inspired numerous case studies, whose insights researchers have distilled into broader, qualitative frameworks for understanding technology transitions. Furthermore, the recent focus on sustainability transitions to counter climate change has led researchers to leverage case studies and qualitative frameworks to gather insights on designing technology policies to stimulate and accelerate these transitions. The *multi-level perspective* (MLP) (Geels, 2002, 2004, 2005) offers a typology by which technology transitions tend to occur. It distinguishes three interacting levels: niches, socio-technical regimes, and an exogenous socio-technical landscape. The socio-technical regime is characterized by path-dependence and lock-in, which are represented in three constituent parts: the socio-technical system, actors, and rules. Systemic developments in the socio-technical landscape are beyond the influence of the regime and are slow to change. When the existing socio-technical regime is replaced by another, a technology transition occurs. Radical innovations, i.e., innovations which are incompatible with the existing socio-technical regime, incubate in niches. In these niches, innovations enjoy protection from market selection and allow the opportunity for the innovation to deviate from the "rules" of the regime, experiment, and learn. For example, Geels (2002) explains how early steamships, while inferior to sailing ships, were adopted by the British Empire's subsidized mail service, which provided opportunities for technological development they would not have otherwise enjoyed. Simultaneous pressure on the regime at the landscape level helps induce a technology transition.

For example, van Bree et al. (2010) operationalize the MLP using a co-evolutionary model to identify scenarios under which alternative fuel vehicles (AFVs), such as hydrogen fuel cell and battery-electric automobiles, are able to achieve a technology transition. The authors identify three barriers to introduction at the niche level: (1) the chicken-and-egg problem, (2) mismatch with consumer preferences, and (3) high cost. These concepts have been central to policy studies and debates in the energy and climate domains, especially assessments of policy prescriptions for accelerating the market penetration of clean technologies (Grubler and Wilson, 2013).

4.2.2 Empirical studies of infrastructure-dependent technology diffusion

The recent literature on the diffusion of infrastructure-dependent technologies contains many empirical case studies and other analyses focusing on alternative fuel vehicles (AFVs), which are particularly relevant to our BEV case study in Section 4.5. For example, Yeh (2007) compares the adoption of natural gas vehicles in eight countries, finding that once natural gas refueling stations reach critical coverage, adoption incentives become more effective. Neaimeh et al. (2017) use a regression model to show that fast chargers may overcome barriers to BEV diffusion, and advocate for policies supporting fast charger deployment. Using an agent-based model for the diffusion of BEVs, Silvia and Krause (2016) find that a hybrid policy of adoption subsidies, expansion of the public charging network, and full electrification of government fleets is the most successful policy for encouraging adoption. In a case study of BEV adoption in Norway, Mersky et al. (2016) discover that access to BEV charging infrastructure, being adjacent to major cities, and incomes have the greatest predictive power for BEV uptake. Based on an agent-based simulation model, van der Vooren et al. (2012) find that policymakers should allocate substantial resources toward public support of infrastructure providers. Certainly, diffusion of AFVs requires large-scale infrastructure investment before adoption can become widespread, and policymakers need to successfully coordinate adoption and infrastructure support. For an excellent review of approaches for modeling the market diffusion of AFVs and their refueling infrastructures, see Gnann and Plötz (2015), which also identifies several general features that are important to include in these models.

Beyond AFVs, the empirical literature examines a variety of other infrastructure-dependent technologies. Gil et al. (2012) present a case study of how novel technologies, such as new designs for aircraft stands and radio frequency identification for baggage handling, were considered in the large-scale, multi-stakeholder infrastructure project of Heathrow Airport's Terminal 5. Wolf and Seebauer (2014) study the adoption of electric bicycles in Austria, finding that adoption depends strongly on ease of use, appropriate infrastructure, and adopters' attitudes toward the environment and physical activity. Suri (2011), employing a data set on maize farmers in Kenya, finds that farmers' adoption of superior hybrid maize and fertilizers is not only driven by higher expected yields, but also by the distribution network for inputs and availability of infrastructure. Leibowicz (2018a) analyzes historical data on the diffusion dynamics of transport systems (canals, railroads, motor vehicles, and airplanes) in the U.S. He documents a consistent pattern whereby the diffusion of infrastructure precedes the adoption of vehicles, which precedes the expansion of travel. This finding highlights the importance of infrastructure provision as a precondition for broad adoption.

4.2.3 Analytical models of infrastructure-dependent technology diffusion

Similar to the pioneering models discussed above (Arthur et al., 1987; Arthur, 1989; Bass, 1969), Brozynski and Leibowicz (in press) model technology diffusion from a top-down perspective, but explicitly incorporate technology policy decision making under uncertainty. To do so, they construct Markov reward process and Markov decision process models that capture policies with different cost structures. The states in the models represent different stages in the diffusion process, and policies are included as costly interventions that raise the probabilities of advancing. The authors derive analytical results and present a case study on lithium-ion batteries for electric vehicles.

A distinct but related branch of the operations research literature models adoption decisions from the bottom-up perspectives of consumers or firms deciding whether or not to adopt a new technology. These models also focus on decision making under uncertainty, but the decisions being analyzed are the strategic adoption choices of individual agents in the market rather than technology policy designs. The studies discussed below all examine the structure of optimal technology adoption decisions and explore how optimal decisions are affected by model parameters. This literature is relevant because the benefits of adoption and their resulting influence on the timing of adoption are important considerations for overcoming the chicken-and-egg problem.

Kornish (2006) constructs a model where an individual considers a choice between two competing technologies that are both subject to positive network effects. In each period, the individual either adopts one of the technologies or opts to wait. While this individual's decisions are explicitly modeled, the behavior of other agents in the market is represented as a nonlinear Polya urn function (Arthur et al., 1987). Committing to a technology entails a key tradeoff. It is better to begin deriving benefits sooner rather than later, but by waiting, the individual can observe which technology is proving to be more popular and thus capture its positive network effects. Kornish finds that the optimal strategy is of a threshold type with respect to the number of previous adopters of each technology. She then explores how stronger network effects influence the optimal strategy. Ulu and Smith (2009) analyze a sequential decision problem in which an individual chooses to adopt a new technology, reject it, or wait under uncertain benefits. When she decides to wait, she obtains a new distribution on the benefits via Bayesian updating. The authors show that a better technology may not actually make the consumer better off once the costs of information gathering and the adoption process are taken into account. Smith and Ulu (2017) extend their earlier analysis by investigating how risk aversion affects the optimal adoption strategy. Finally, Smith and Ulu (2012) compare and contrast three models (net present value, single-purchase, and repeat-purchase) of an individual's technology adoption decision under uncertain future costs and quality, modeled as Markov process transitions. They find that in the repeat-purchase or "upgrades" model, technological improvements that make the consumer better off may actually discourage adoption.

4.2.4 Game-theoretic models of infrastructure-dependent technology diffusion

Methodologically, the studies in the literature which are most closely related to our own are those that use game-theoretic (i.e., multi-agent) models to represent the interactions between a policymaker and market agents. Some of these specifically model a policymaker and a profit-maximizing firm. Alizamir et al. (2016) assess the design of cost-effective and socially optimal feed-in tariff policies intended to stimulate the diffusion of renewable electricity technologies. In their modeling framework, the policymaker commits to a sequence of time-specific contract prices, and heterogeneous investors decide whether and when to invest in the renewable technology. Their approach also captures positive reinforcement mechanisms that are characteristic of diffusion processes, including investment costs that are determined endogenously via a nonlinear learning curve, and information contagion effects wherein the number of uninformed investors who become active at time t is proportional to the cumulative installed capacity at time $t-1$. Because the purported goal of a typical feed-in tariff program is to incentivize diffusion of the renewable technology, the authors explore two objectives for the policymaker, one in which an exogenous adoption target must be reached at the lowest possible cost, and another in which grid parity must be achieved at the end of the time horizon and social welfare is maximized. Their findings provide partial justification for current feed-in tariff implementations, but suggest that the current practice of maintaining constant profitability for investors is rarely optimal.

Chemama et al. (2019) similarly explore optimal supply-side policy, in which the policymaker reduces the supplier's production cost via a production subsidy over two periods in order to reach an endogenously defined level of adoption while minimizing the subsidy program cost. The suppliers respond with profit-maximizing production quantities by solving a multi-period newsvendor problem. Their study specifically examines the tradeoff between committing to a time-specific subsidy plan up front versus a flexible policy that adapts after uncertain demand is realized. Indeed, the anticipation of a policy revision lowers the supplier's production target and may increase the total subsidy program cost. Their analytical results indicate that when the policymaker commits to a fixed policy, it encourages suppliers to produce earlier, and additional spending reduces adoption level uncertainty. Finally, they present a case study on an existing solar subsidy program.

While the studies above investigate optimal supply-side policies, Cohen et al. (2016) analyze how to optimally set *consumer* subsidies under demand uncertainty. In their two-stage Stackelberg game, the policymaker minimizes the expected subsidy program cost to satisfy an exogenous adoption target by announcing a consumer subsidy for a product offered by the manufacturer. The manufacturer is a price-setting newsvendor who maximizes profit in response. They find that if the policymaker ignores demand uncertainty, she will under-subsidize and miss the desired adoption target. Moreover, the authors demonstrate that consumer subsidies are a sufficient mechanism to coordinate the policymaker and manufacturer, i.e., prices and quantities coincide in a decentralized model (independent, profit-maximizing manufacturer) and a centralized model (a central planner makes the price and quantity decisions). Using a similar Stackelberg game methodology, Bian and Zhao (2020) evaluate different supply-side policy instruments by comparing an environmental subsidy based on a manufacturer's emissions abatement to an emissions tax levied on the manufacturer based on its emissions. They find that the manufacturer performs better under the subsidy program, but that the net emissions are higher than under the tax program if abatement is costly and emissions sufficiently damaging.

In contrast to the studies discussed above, which focus on either supply- or demand-side policy, our model incorporates both. Similarly, Yu et al. (2018) use a game-theoretic framework to model the strategic interactions among three players – a policymaker, manufacturers, and consumers – where the policymaker determines both manufacturer and consumer subsidies to maximize consumer welfare subject to a policy budget constraint. They find that in order to maximize consumer welfare, it is optimal to only subsidize customers when the product has a well established market price, but otherwise subsidize manufacturers. The papers most directly related to ours involve a responsive private industry player who makes infrastructure investment decisions, rather than product manufacturing decisions. Along these lines, Ma et al. (2019) explore whether product subsidies and service infrastructure subsidies are complementary or substitute instruments for a policymaker. Their model is a multi-period Stackelberg game in which a monopolistic firm responds to the policymaker's subsidies by choosing the quantity of clean technology to supply as well as making a binary decision on whether to invest in service infrastructure that benefits the clean technology product. The consumer in turn decides whether and in which stage to adopt the technology. As in our model, the policymaker maximizes utility, accounting for the benefits to the environment of clean technology adoption and the policy expenditure. They find that the optimal subsidy strategy follows a sandwich rule in which the policymaker subsidizes infrastructure and consumers if the infrastructure deployment cost is moderate, but otherwise subsidizes the consumers only. Additionally, if the investment cost is sufficiently low, the firm supplies infrastructure even without a subsidy and therefore the policymaker prefers to subsidize the consumer only. Ji and Huang (2018) also develop a model which is similar in spirit to ours. They present a two-stage Stackelberg game, specific to electric vehicle adoption, where a policymaker decides on price subsidies for consumers and production subsidies for a provider of charging stations. Due to the computational complexity of their modeling approach, their results are limited to numerical simulations and do not appear to be solved optimally. Rather, the policymaker's decision variables are modulated and the best simulated solutions are reported.

Several other studies use game theory principles to analyze the interactions among policymaker, profit-maximizing firms, and adopters. Yu et al. (2016) model the diffusion of BEVs as a two-player sequential game between potential adopters and a profit-maximizing charging infrastructure firm. As the leader, the firm maximizes profit by choosing among a set of potential sites where it can invest in charging infrastructure, and on prices for charging. The authors obtain a threshold rule for the optimal purchasing decision and a closed form expression for the BEV market share. Furthermore, the number of charging stations the firm optimally deploys increases when a welfare-maximizing social planner determines the set of charging station locations to build by regulation. The effects of adoption and investor subsidies are considered via exogenous sensitivity analysis, indicating that consumers' sensitivity to price determines whether adoption or investor subsidies are preferred. Encarnação et al. (2018) formulate an evolutionary game theory (EGT) model of BEV diffusion in which governments, private suppliers, and consumers each choose whether to cooperate (support BEVs) or defect (not support BEVs), and an equilibrium in mixed strategies is a representation of BEV market share. Most importantly, they find that it is most efficient for demand for BEVs to precede supply and that reaching full adoption requires coordination across the three sectors. Their model is an analytical framework based on a population dynamics EGT model, but does not strictly determine optimal policy.

This review of the literature reveals the need for a general, theoretical model for the diffusion of infrastructure-dependent technologies, and analytical insights on technology policies for overcoming the chicken-and-egg problem. The following section presents the bilevel model that we develop to address this gap in the literature.

4.3 Methodology

We formulate a stylized model of technology policy decision making from the perspective of a policymaker who seeks to stimulate the market penetration of an infrastructure-dependent technology. Our model is a bilevel optimization problem in which a policymaker (leader) maximizes net social benefits by setting the levels of two incentives: a subsidy for a profit-maximizing firm (follower) to invest in infrastructure that raises the benefit of adoption to consumers, and a direct subsidy for consumers to adopt the technology. Consumer uptake is then a function of the firm's infrastructure provision and the direct subsidy for consumer purchases. The policymaker's objective consists of benefits which scale with the level of adoption, minus the costs of the policy incentives themselves.

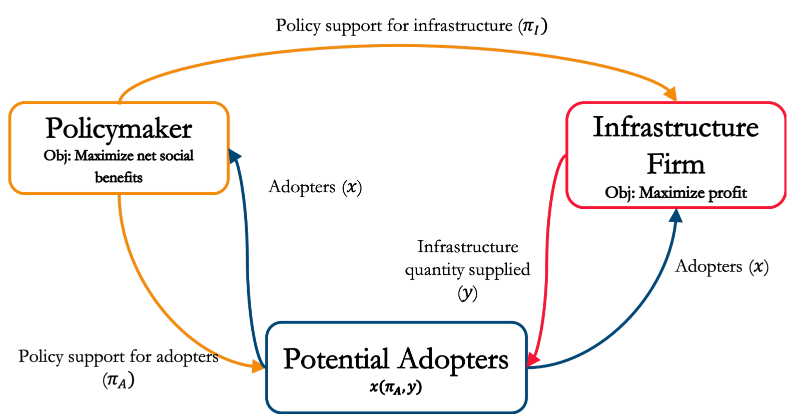

Figure 4.1. High-level model overview. Arrows represent the mechanisms through which each player influences other players' decision making problems (policymaker and infrastructure firm) or endogenous outcomes (adopters).

Figure 4.1 provides a high-level visual overview of the model, including its endogenous variables and the ways that the players influence one another. The policymaker, who acts first, can employ two types of financial incentives, illustrated as the orange arrows in Figure 4.1. First, the policymaker can indirectly stimulate adoption by providing a per-unit investment cost subsidy π_I (in \$/unit) for the infrastructure firm. Under the right market conditions, this investment subsidy reduces the infrastructure firm's marginal cost, thereby increasing its optimal level of infrastructure investment y. As illustrated by the red arrow in the figure, higher infrastructure investment by the firm induces greater consumer adoption of the technology. This is why we refer to the infrastructure subsidy π_I as an indirect mechanism for promoting consumer adoption, since it must first "pass through" the infrastructure firm's decision making before influencing consumers. Second, the policymaker can directly stimulate adoption by offering consumers a per-unit adoption subsidy π_A (in \$/unit). Taken together, the policy allocation (π_A, π_I) is chosen to maximize net social benefits, where benefits are proportional to adoption $x(\pi_A, y)$, minus the costs of the incentives themselves. According to the bilevel formulation, the policymaker is assumed to have complete knowledge of the infrastructure firm's problem and is able to perfectly anticipate $y^*(\pi_A, \pi_I)$, the firm's profit-maximizing infrastructure investment response to any policy allocation.

We now present the mathematical formulation, beginning with the representation of adoption and moving upward to the infrastructure firm's problem and then the full bilevel model.

4.3.1 The adoption level

As described above, the adoption subsidy and quantity of infrastructure provided determine the level of adoption, which we denote as $x(\pi_A, y)$. We define the adoption level, which is measured in absolute units (e.g., thousands of adopters), as

$$x(\pi_A, y) = \beta_c \pi_A + \beta_b y(\pi_A, \pi_I) + K. \tag{4.1}$$

The number of adopters is therefore a linear function of (1) the adoption subsidy offered by the policymaker, π_A; (2) the amount of infrastructure provided by the infrastructure firm, $y(\pi_A, \pi_I)$; and (3) a constant term, K, to reflect, for example, "innovator adopters" who would purchase the technology without any subsidy or infrastructure available.[1] The interpretation of the coefficients is straightforward: $\beta_c > 0$ represents the additional adopters resulting from a unit increase in the adoption subsidy, whereas $\beta_b > 0$ represents the additional adopters resulting from a unit increase in infrastructure investment. Broadly, β_c and β_b measure the sensitivity of the adoption level to the cost and benefit of the technology, respectively. In other words, the adoption subsidy reduces the cost of the technology, while infrastructure investment enhances the benefits of adoption. Indeed, the subscripts c and b refer to the cost and benefit terms in the adoption level function.

4.3.2 The infrastructure firm's problem

Consistent with the bilevel structure of our model, we first describe the lower-level problem solved by the infrastructure firm, since its optimal solution will be anticipated by the policymaker in the upper-level problem. The infrastructure firm is represented as a monopolist who sets the price of using the infrastructure. Having observed the policymaker's incentives, the firm

[1] A linear function is chosen for analytical tractability and straightforward implementation in a case study. For example, numerous empirical studies have used linear regression to estimate the effects of various factors on BEV adoption, and we use these to parameterize our case study in Section 4.5. Nevertheless, we acknowledge that assuming a linear relationship entails a loss of generality.

chooses the profit-maximizing level of infrastructure investment. The firm faces constant marginal cost $c - \pi_I$, where c is the per-unit cost of building infrastructure and π_I is the policymaker's infrastructure subsidy. The firm's revenue function needs to reflect that, as the number of adopters changes, so too should the demand curve for use of the infrastructure. Mathematically, the price of the infrastructure service is represented as a function $p(x, y)$, which is increasing in the number of adopters x (shift of the demand curve) and decreasing in the amount of infrastructure y (movement along the demand curve). However, because the firm has some ability to affect the market size through the $\beta_b y(\pi_A, \pi_I)$ term in Eq. (4.1), a tension emerges. Investing in more infrastructure simultaneously raises the market price because it increases the number of adopters who use the infrastructure, but reduces the market price because the demand curve is downward-sloping. Ultimately, the price function $p(x, y)$ must be decreasing in the quantity of infrastructure to ensure a valid profit maximization problem. To capture these competing mechanisms, we require a well-defined relationship among the market price of the infrastructure service, the quantity of infrastructure built, and the number of adopters. The adoption level $x(\pi_A, y)$ is related to the inverse demand curve for infrastructure service $p(\cdot)$ and the infrastructure investment $y(\pi_A, \pi_I)$ through

$$x(\pi_A, y) = ap(\cdot) + by(\pi_a, \pi_I), \text{ where } a, b > 0. \tag{4.2}$$

By substituting the definition of $x(\pi_A, y)$ from Eq. (4.1) into Eq. (4.2) and rearranging, we obtain the inverse demand curve

$$p(y) = \frac{\beta_c \pi_A + K}{a} - \frac{b - \beta_b}{a} y. \tag{4.3}$$

It is necessary to assume that $b - \beta_b > 0$, for otherwise the inverse demand curve would not be downward-sloping; indeed, the difference $b - \beta_b$ reflects the competing mechanisms discussed above that determine the behavior of the market price for infrastructure use. Looking at Eq. (4.3), we can see how each parameter affects the demand curve. First, increasing β_c, π_A, or K shifts the linear inverse demand curve upward. That is, if the parameters lead to an exogenous increase in the number of adopters – whether through greater sensitivity to the adoption subsidy (β_c), a higher adoption subsidy (π_A), or a higher number of innovator adopters (K) – the infrastructure firm enjoys a higher price for the same level of investment. Second, if potential adopters' sensitivity to infrastructure provision (β_b) increases, the firm enjoys a higher price for the same level of investment, and this price differential is magnified at higher levels of investment (i.e., the linear inverse demand curve rotates upward around the price-axis intercept). Finally, Eq. (4.3) reveals the roles that parameters a and b play in determining the behavior of the inverse demand curve. Parameter b only appears in its slope coefficient. Increasing b implies a steeper slope, reducing the price of the infrastructure service. Increasing a implies a flattening of the demand curve, whereby the price is reduced at lower levels of infrastructure provision but raised at higher levels of infrastructure provision.

Assembling all these components together, the infrastructure firm's problem is

$$\max_{y(\pi_A,\pi_I)\geq 0} p(y)y - (c - \pi_I)y = \max_{y(\pi_A,\pi_I)\geq 0} \left[\frac{\beta_c \pi_A + K}{a} - \frac{b - \beta_b}{a} y\right] y - (c - \pi_I)y. \tag{4.4}$$

The infrastructure provision decision variable, which must be non-negative, is written as $y(\pi_A, \pi_I)$ to remind readers that it is chosen in response to the upper-level policy allocation.

4.3.3 The bilevel optimization model

The policymaker chooses the allocation (π_A, π_I) to maximize the social benefits of adoption, less the costs of the incentives themselves. The cost of the policy allocation is $x(\pi_A, y)\pi_A + y(\pi_A, \pi_I)\pi_I$, where the first term is the expenditure on consumer adoption subsidies (total adoption policy cost) and the second term is the expenditure on infrastructure investment subsidies (total infrastructure policy cost). It is important to emphasize that, because the policy decisions π_A and π_I influence the endogenous levels of adoption and infrastructure provision, they entail both direct and indirect costs. The adoption subsidy π_A has a direct cost, but it also influences the number of adopters, which in turn influences the quantity of infrastructure built, thereby affecting both the total adoption policy cost and the total infrastructure policy cost. Similarly, the infrastructure subsidy π_I has a direct cost, but also influences the firm's infrastructure provision, which in turn influences the number of adopters, thereby also affecting both the total adoption policy cost and the total infrastructure policy cost. This discussion highlights the interdependence of the two policy instruments, with numerous feedback mechanisms determining their joint costs and benefits. In practice, it is essential for the policymaker to account for their interdependent nature.

We assume that the social benefit is simply proportional to the number of adopters, where the parameter α captures the marginal social benefit of each additional adopter. For example, to preview our BEV case study in Section

4.5, a policymaker could view α as the monetary reduction in the social cost of greenhouse gas (GHG) emissions resulting from the replacement of a gasoline vehicle by a BEV.

Finally, the upper-level problem entails a few straightforward constraints. First, the adoption and infrastructure subsidies need to be non-negative. Second, the infrastructure subsidy π_I cannot exceed the marginal infrastructure investment cost c, for otherwise the firm would face a negative cost. Third, in line with the bilevel framework, the infrastructure firm's optimal response serves as a constraint in the policymaker's problem. The full specification of the bilevel optimization problem is

$$\begin{aligned} z^* = \max_{\pi_A, \pi_I} \quad & \alpha(\beta_c \pi_A + \beta_b y + K) - \left[(\beta_c \pi_A + \beta_b y + K)\pi_A + y\pi_I\right], \\ \text{s.t.} \quad & \pi_A \geq 0, \\ & \pi_I \geq 0, \\ & \pi_I \leq c, \\ & \max_{y(\pi_A, \pi_I) \geq 0} \quad \left[\tfrac{\beta_c \pi_A + K}{a} - \tfrac{b - \beta_b}{a} y\right] y - (c - \pi_I) y. \end{aligned} \tag{4.5}$$

Reflecting on the formulation, it is important to emphasize that our cost-benefit paradigm allows the policymaker flexibility to determine the total amount of public funds to dedicate to supporting the diffusion of this technology, in addition to the decision about how to divide them between two incentives. Alternative formulations could include a cost-effectiveness approach that determines the least costly policy allocation that induces a desired adoption level, or a pure resource allocation problem structured to maximize adoption (and thus benefits) by dividing a fixed budget between the two policy channels. Of these alternatives, we consider our cost-benefit framework the most comprehensive in terms of its ability to inform policy.

Before proceeding, it is worth acknowledging some of the main limitations of our stylized model. First, we only consider two specific forms of technology policy intervention which are both financial subsidies. There are many other monetary and non-monetary policy instruments available in the real world which are outside the scope of the model. Second, our model is a static sequential game. There is no representation of time, and therefore no strategic decision making from one period to the next as the diffusion process evolves dynamically. Third, our model is deterministic. In a broad sense, technology transitions are subject to many uncertainties that powerfully influence their prospects for success. In a narrower sense, policy interventions targeting firms and consumers can have stochastic outcomes, as their responses are often difficult to predict. Fourth, the bilevel framework inherently assumes that the policymaker has complete knowledge of the infrastructure firm's problem. In reality, policymakers are usually unable to observe firms' own costs, demand curves, and so on. Fifth, as previously mentioned, the model assumes that several relationships are linear to ensure analytical tractability and compatibility with empirical studies that have estimated parameters for case study applications. Despite these limitations, our bilevel model is highly general and is able to yield analytical insights, which we derive in the next section.

4.4 Analysis

4.4.1 Solution to the infrastructure firm's problem

In the lower-level problem, the infrastructure firm chooses how much infrastructure to invest in, $y(\pi_A, \pi_I)$, in response to the policy allocation (π_A, π_I) chosen by the policymaker, in order to maximize its profit. We denote by $y^*(\pi_A, \pi_I)$ the *optimal response* to the policymaker's decisions, since the firm's revenue and cost are affected by the subsidy levels.

From the inverse demand curve in Eq. (4.3), the firm's marginal revenue is $MR = \frac{\beta_c \pi_A + K}{a} - \frac{2(b-\beta_b)}{a} y$, which decreases linearly with y. The firm's marginal cost is $MC = c - \pi_I$, which is constant. Equating marginal revenue with marginal cost, we obtain $y^*(\pi_A, \pi_I) = \frac{-a(c-\pi_I)+\beta_c\pi_A+K}{2(b-\beta_b)}$. To ensure non-negativity, we require $-a(c - \pi_I) + \beta_c \pi_A + K \geq 0$. Rearranging, this non-negativity condition is equivalent to $\frac{\beta_c \pi_A + K}{a} \geq c - \pi_I$. In Proposition 4.1, we completely specify the firm's optimal response $y^*(\pi_A, \pi_I)$.

Proposition 4.1. *The infrastructure firm's optimal response is*

$$y^*(\pi_A, \pi_I) = \begin{cases} \frac{-a(c-\pi_I)+\beta_c\pi_A+K}{2(b-\beta_b)}, & \textit{if } \frac{\beta_c\pi_A+K}{a} \geq c - \pi_I, \\ 0, & o.w. \end{cases}$$

Proof. See Appendix C.2.1.

Interpreted through the $MR = MC$ condition, the non-negativity condition says that the positive (constant) term of the firm's marginal revenue (i.e., $\frac{\beta_c\pi_A+K}{a}$) must exceed the marginal cost; otherwise, marginal cost would always exceed marginal revenue and the firm's optimal response would be $y^*(\pi_A, \pi_I) = 0$. We note that this condition involves the upper-level decision variables (π_A, π_I), reflective of the influence that the policymaker's decisions have on the firm's optimal response. For example, when the policymaker increases π_A, the demand curve shifts upward, in turn raising the firm's marginal revenue. Because marginal cost is constant, the firm responds by increasing its infrastructure investment to reach the $MR = MC$ condition; indeed, by examining the comparative statics of $y^*(\pi_A, \pi_I)$, we see this positive relationship (i.e., $\frac{\partial y^*(\pi_A,\pi_I)}{\partial \pi_A} > 0$). When the policymaker increases π_I, the firm's marginal cost decreases, leading the firm to increase infrastructure investment until the $MR = MC$ condition is reached. Again, by examining the comparative statics of $y^*(\pi_A, \pi_I)$, we see this positive relationship (i.e., $\frac{\partial y^*(\pi_A,\pi_I)}{\partial \pi_I} > 0$).

If the policymaker does not choose a policy allocation that allows the $MR = MC$ condition to be satisfied, then the firm's optimal response is $y^*(\pi_A, \pi_I) = 0$. Finally, we note that the policymaker choosing $\pi_I = c$ does not create a mathematical or economic anomaly. While the firm's marginal cost at this choice is 0 – in other words, it can scale investment y to infinity at zero cost – it still faces a downward-sloping demand curve and therefore chooses the quantity (or equivalently, price) to satisfy the $MR = MC$ condition. This occurs at investment level $y^*(\pi_A, \pi_I = c) = \frac{\beta_c \pi_A + K}{2(b-\beta_b)}$.

4.4.2 Reformulation of the bilevel model into a quadratic program

Proposition 4.1 specifies the firm's optimal response $y^*(\pi_A, \pi_I)$. If the policy allocation is chosen such that the $-a(c - \pi_I) + \beta_c \pi_A + K \geq 0$ condition holds strictly, then the firm supplies a positive quantity of infrastructure. Hence, we refer to this condition as the *inducement condition*, as it is necessary and sufficient to induce the firm to invest in infrastructure. In this section, we show that the bilevel optimization model is equivalent to a quadratic program that can be convex or non-convex depending on the parameters.

To solve the policymaker's upper-level problem and ultimately determine an equilibrium, we construct two distinct optimization programs, in which (1) the policymaker chooses an allocation (π_A, π_I) such that it is not optimal for the firm to invest, and (2) the policymaker chooses an allocation such that it could be optimal for the firm to invest in infrastructure. We refer to these as the *non-inducement* and *inducement* programs, respectively, with optimal objective values z^*_{NI} and z^*_I. Each program corresponds to one of the two cases outlined in Proposition 4.1, distinguished by whether the inducement condition is satisfied or not. By dividing the upper-level problem into these two cases, we can directly substitute the corresponding optimal response $y^*(\pi_A, \pi_I)$ into the policymaker's objective function, thus converting the bilevel program into a single-level optimization problem. It follows, then, that the optimal solution to the policymaker's problem is found by comparing the solutions to the non-inducement and inducement programs, and choosing the policy allocation that yields the higher objective function value. Mathematically, the optimal solution to the bilevel model of Eq. (4.5) is $z^* = \max(z^*_{NI}, z^*_I)$.

It is not necessarily suboptimal for the policymaker to choose an allocation such that the firm does not invest in infrastructure. As described in Section 4.3.3, when the firm invests in infrastructure, it directly increases the total infrastructure policy cost, and indirectly increases the total adoption policy cost, borne by the policymaker. Depending on the parameter values, these additional costs of inducing infrastructure investment may or may not be justified by the resulting social benefits.

In the *non-inducement* program,

$$
\begin{array}{rrcl}
z^*_{NI} = \max\limits_{(\pi_A,\pi_I)} & -\beta_c \pi_A^2 + (\alpha\beta_c - K)\pi_A + \alpha K, & & \\
\text{s.t.} & \frac{\beta_c \pi_A + K}{a} & \leq & c - \pi_I, \\
 & \pi_A & \geq & 0, \\
 & \pi_I & \geq & 0, \\
 & \pi_I & \leq & c,
\end{array}
\tag{4.6}
$$

the policymaker is constrained to choose a policy allocation (π_A, π_I) such that the inducement condition is not satisfied and the firm's optimal response is $y^*(\pi_A, \pi_I) = 0$. In this case, we have reformulated the bilevel model by applying backwards induction, substituting the optimal response $y^*(\pi_A, \pi_I) =$

0 into the policymaker's objective function, and noting immediately that the infrastructure subsidy decision variable π_I does not appear in the objective function. This is intuitive; conditional on the firm not being induced to invest in infrastructure, the level of the infrastructure subsidy is irrelevant. In addition to the bounds on π_A and π_I, we also ensure that the firm's optimal response cannot be positive.

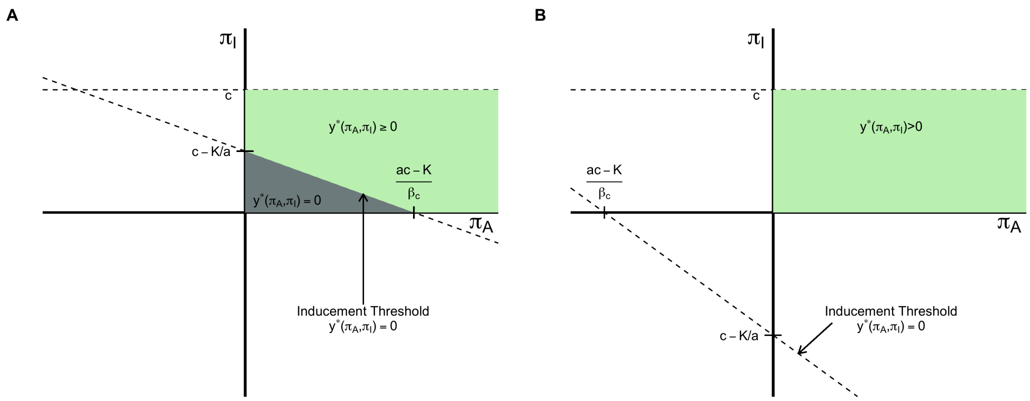

Figure 4.2. Illustrations of the feasible regions of the non-inducement (gray area) and inducement (green area) programs in two cases. The non-inducement program is feasible in case (A) but infeasible in case (B).

Now, we investigate whether the non-inducement program in Eq. (4.6) is even feasible. This depends on where the inducement threshold line lies in relation to the bounds on π_A and π_I. In Figure 4.2, we illustrate the two possible cases. In Figure 4.2A, the feasible region of the non-inducement program is denoted by the gray shaded area (within the non-negativity bounds and beneath the inducement threshold). In Figure 4.2B, the inducement threshold lies below and to the left of the origin. Where the inducement threshold lies, and specifically whether or not it passes through the positive quadrant, depends on the sign of $c - \frac{K}{a}$. Examining Figure 4.2 and the firm's optimal response given in Proposition 4.1, we see that $c - \frac{K}{a}$ reflects the market conditions facing the firm and the per-unit infrastructure investment cost c. If $c - \frac{K}{a} < 0$, then the firm will invest in infrastructure regardless of the policymaker's allocation (π_A, π_I), even if it is $(0, 0)$ and there are no subsidies. This is demonstrated in Figure 4.2B; the non-inducement program is in fact infeasible and any feasible solution to the inducement program (green area) is guaranteed to include positive infrastructure investment. We can intuitively interpret why the comparison between c and $\frac{K}{a}$ determines whether infrastructure investment is guaranteed even in the absence of policy incentives. This will be true if the price-axis intercept of the infrastructure firm's demand curve (marginal revenue) lies above the flat marginal cost curve. Having more innovator adopters (higher K) or a lower a value both raise marginal revenue, and having a lower infrastructure investment cost c shifts the flat marginal cost curve downward. Both of these effects favor having an $MR = MC$ intersection in the positive quadrant. In other words, $\frac{K}{a}$ is the largest per-unit investment cost for which the firm finds it profitable to supply infrastructure in the absence of policy intervention. If c exceeds $\frac{K}{a}$, then the firm will not invest in infrastructure without policy support. Remark 4.1 summarizes this case.

Remark 4.1. *If $c - \frac{K}{a} < 0$, then the non-inducement program is infeasible, the inducement program is feasible, and by elimination, $z^* = z_I^*$.*

Next, we examine the case where the non-inducement program is feasible, that is, when $c - \frac{K}{a} > 0$, as illustrated by the gray area in Figure 4.2A. In Eq. (4.6), we see that π_I does not affect the objective z_{NI}^* and so can be set to $\pi_I = 0$, which leads to the widest possible feasible region for π_A; the lower and upper bound constraints $0 \leq \pi_I \leq c$ can also be safely eliminated, yielding

$$\begin{array}{rll} z^*_{NI} = \max\limits_{\pi_A} & -\beta_c \pi_A^2 + (\alpha\beta_c - K)\pi_A + \alpha K, & \\ \text{s.t.} & \pi_A \;\leq\; \frac{ac-K}{\beta_c}, & \\ & \pi_A \;\geq\; 0, & \end{array} \tag{4.7}$$

whose objective function attains a local maximum at $\pi_A = \frac{\alpha\beta_c - K}{2\beta_c}$. To then determine the optimal solution to the non-inducement program, we simply compare this local maximum with the objective values at the lower and upper bounds for π_A. Remark 4.2 summarizes the cases.

Remark 4.2. *If $c - \frac{K}{a} \geq 0$, the solution to the non-inducement program in Eq. (4.7) is*

$$\pi_A^* = \begin{cases} \frac{ac-K}{\beta_c}, & \textit{if } \frac{ac-K}{\beta_c} \leq \frac{\alpha\beta_c - K}{2\beta_c}, \\ \frac{\alpha\beta_c - K}{2\beta_c}, & \textit{if } 0 \leq \frac{\alpha\beta_c - K}{2\beta_c} \leq \frac{ac-K}{\beta_c}, \\ 0, & \textit{o.w.} \end{cases}$$

Remark 4.2 shows that there are three possible candidate solutions to the non-inducement program, depending on the parameterization. Because π_I disappears from the policymaker's objective function if $y^*(\pi_A, \pi_I) = 0$, the inducement program captures the same market outcome as the non-inducement program along the inducement threshold line. For example, if the optimal solution to the non-inducement program is $\pi_A^* = \frac{\alpha\beta_c - K}{2\beta_c}$, then the point $(\pi_A, \pi_I) = \left(\frac{\alpha\beta_c - K}{2\beta_c}, c - \frac{\alpha\beta_c + K}{2a}\right)$ is feasible in the inducement program (it lies on the inducement threshold line) and has the same objective value as $(\pi_A, \pi_I) = \left(\frac{\alpha\beta_c - K}{2\beta_c}, 0\right)$ in the non-inducement program. In other words, for every feasible solution π_A in the non-inducement program, we can draw a vertical line from the point $(\pi_A, \pi_I = 0)$ to the inducement threshold such that every point along this line has the same objective value. Essentially, the non-inducement program is redundant, as the inducement program captures the possibility of the policymaker choosing the allocation such that $y^*(\pi_A, \pi_I) = 0$ because its feasible region includes the inducement threshold line. This concept is summarized in Remark 4.3, which says that, if $c - \frac{K}{a} \geq 0$, then the solution to the non-inducement program gives a lower bound on the policymaker's objective value in the bilevel model.

Remark 4.3. *If $c - \frac{K}{a} \geq 0$, then $z^*_{NI} \leq z^*_I$. Therefore, $z^* = z^*_I$.*

Combining the results from Remarks 4.1 – 4.3, we have shown that the general bilevel model given in Eq. (4.5) is mathematically equivalent to the inducement program, which is written in Proposition 4.2.

Proposition 4.2. *The general bilevel model from Eq. (4.5) is equivalent to the quadratic program*

$$
\begin{array}{rrcl}
z^* = \max\limits_{\boldsymbol{\pi}=(\pi_A,\pi_I)} & \frac{1}{2}\boldsymbol{\pi}^T \boldsymbol{H} \boldsymbol{\pi} + \boldsymbol{g}^T \boldsymbol{\pi}, & & \\
s.t. & \frac{\beta_c \pi_A + K}{a} & \geq & c - \pi_I, \\
& \pi_A & \geq & 0, \\
& \pi_I & \geq & 0, \\
& \pi_I & \leq & c,
\end{array}
\tag{4.8}
$$

where the Hessian $\boldsymbol{H} = \begin{pmatrix} -2\beta_c - \frac{2\beta_b\beta_c}{2(b-\beta_b)} & \frac{-\beta_b a - \beta_c}{2(b-\beta_b)} \\ \frac{-\beta_b a - \beta_c}{2(b-\beta_b)} & \frac{-2a}{2(b-\beta_b)} \end{pmatrix}$ *and*

$\boldsymbol{g} = \begin{pmatrix} \alpha\beta_c + \frac{\alpha\beta_b\beta_c}{2(b-\beta_b)} - \frac{\beta_b(K-ac)}{2(b-\beta_b)} - K \\ \frac{\alpha\beta_b a}{2(b-\beta_b)} - \frac{\alpha\beta_b(K-ac)}{2(b-\beta_b)} + \alpha K \end{pmatrix}.$

Proof. See Appendix C.2.2.

The quadratic program (QP) in Eq. (4.8) has just two variables and only linear constraints. While it is a small problem, we would like to establish whether or not it is convex. If it is a convex QP, then that would guarantee that any local maximum is also the global maximum, and make the program easy to solve using interior point methods encoded in many commercial solvers. It turns out that our QP is non-convex in general, although it can be convex depending on the parameter values. In Proposition 4.3, we provide a necessary and sufficient condition for convexity. In the next section, we discuss the implications of non-convexity for guaranteeing that we obtain the global maximum, and develop a custom solution strategy to bypass the non-convexity issue.

Proposition 4.3. *The quadratic program in Eq. (4.8) is convex if and only if* $8\beta_c ab - 6\beta_b\beta_c a \geq \beta_b^2 a^2 + \beta_c^2$.

Proof. See Appendix C.2.3

4.4.3 Custom solution strategy

As summarized in Proposition 4.3, our QP reformulation of the bilevel model is non-convex in general, which raises practical concerns about being able to guarantee a globally optimal solution. Indeed, many commercial and open-source solvers may only identify a local maximum, or otherwise fail to return a solution.[2] Furthermore, first-order Karush-Kuhn-Tucker conditions may not be sufficient conditions for a global maximum under non-convexity. To circumvent the complications of solving a non-convex program, we develop a custom solution strategy that guarantees global optimality. This solution strategy, which is presented below, entails the evaluation of four single-variable QPs.

[2] The commercial solver Gurobi 9.0, which is invoked for comparison in Section 4.5, employs a bilinear branch-and-bound technique by which non-convex QPs can be solved to global optimality.

For clarity of exposition, we can rewrite the QP from Eq. (4.8) as

$$
\begin{aligned}
z^* = \max_{\pi_I} \quad & h_1\pi_A^2 + h_2\pi_I^2 + h_3\pi_A\pi_I + h_4\pi_A + h_5\pi_I + h_6, \\
\text{s.t.} \quad & \tfrac{\beta_c\pi_A + K}{a} \geq c - \pi_I, \\
& \pi_A \geq 0, \\
& \pi_I \geq 0, \\
& \pi_I \leq c,
\end{aligned}
\tag{4.9}
$$

where $h_1 < 0$, $h_2 < 0$, and $h_3 < 0$, but the signs of the remaining coefficients h_4, h_5, and h_6 are a priori indeterminate and therefore depend on the particular parameterization of the model. See C.1 for algebraic expressions for these coefficients in terms of the fundamental parameters.

Our solution strategy begins with a reduction of the two-variable QP into a single-variable QP in which the π_I variable is fixed. By fixing π_I, and rearranging the objective function by removing the constant terms $h_2\pi_I^2 + h_5\pi_I + h_6$, we arrive at the *conditional problem*

$$
\begin{aligned}
z^*(\pi_I) = h_2\pi_I^2 + h_5\pi_I + h_6 + \max_{\pi_A} \quad & h_1\pi_A^2 + (h_3\pi_I + h_4)\pi_A, \\
\text{s.t.} \quad & \tfrac{\beta_c\pi_A + K}{a} \geq c - \pi_I, \\
& \pi_A \geq 0,
\end{aligned}
\tag{4.10}
$$

in which π_A is the decision variable and the objective is maximized given the fixed value of π_I. This conditional model of Eq. (4.10), in which π_I is treated as a parameter, is always feasible and always convex. The point $\pi_A = \max\left(\frac{a(c-\pi_I)-K}{\beta_c}, 0\right)$ lies in the feasible region $\forall\ \pi_I$ such that $0 \leq \pi_I \leq c$, and $h_1 < 0$ implies convexity.

The solution to the conditional problem of Eq. (4.10) can be used to determine the solution to the original problem of Eq. (4.8) (which we will hereafter refer to as the *unconditional problem*) by noting that

$$
z^* = \max_{0 \leq \pi_I \leq c} z^*(\pi_I). \tag{4.11}
$$

That is, $z^*(\pi_I)$ is the optimal objective value for a particular π_I, and the unconditional problem selects the $\pi_I \in [0, c]$ that yields the largest optimal objective value in the conditional model.

Our solution strategy proceeds by determining the analytical solution to the conditional problem, $\pi_A^*(\pi_I)$ with optimum $z^*(\pi_I)$, which we then substitute into the unconditional problem of Eq. (4.11). We obtain a single-variable QP (π_A is eliminated) with linear constraints that is equivalent to the original two-variable quadratic model of Eq. (4.8).

With the approach laid out, we now derive the analytical solution to the conditional problem. Intuitively, since the cross-product term $\pi_A\pi_I$ appears in Eq. (4.9), the fixed level of π_I affects both the feasible region (through the inducement threshold constraint) and the objective function (through the linear term) of Eq. (4.10). We therefore begin by determining how the sign of the linear term, $h_3\pi_I + h_4$, affects the optimal solution $\pi_A^*(\pi_I)$. First, if $h_3\pi_I + h_4 \leq 0$, the maximum of the concave objective function occurs at a $\pi_A < 0$ and the function decreases monotonically for $\pi_A \geq 0$. So, in this case, the optimal solution $\pi_A^*(\pi_I)$ is at whichever of the two bounds ($\pi_A \geq 0$ or $\pi_A \geq \frac{ac-K-a\pi_I}{\beta_c}$) is stricter, as in,

$$\pi_A^*(\pi_I) = \begin{cases} 0, & \text{if } ac - K - a\pi_I \leq 0, \\ \frac{ac-K-a\pi_I}{\beta_c}, & \text{o.w.} \end{cases} \tag{4.12}$$

In the case $h_3\pi_I + h_4 > 0$,

$$\pi_A^*(\pi_I) = \begin{cases} \frac{-h_3\pi_I - h_4}{2h_1}, & \text{if } \frac{-h_3\pi_I-h_4}{2h_1} \geq \frac{ac-K-a\pi_I}{\beta_c}, \\ \frac{ac-K-a\pi_I}{\beta_c}, & \text{o.w.}, \end{cases} \tag{4.13}$$

solves Eq. (4.10). Here, the local maximum of the objective function, which is attained at $\pi_A = \frac{-h_3\pi_I-h_4}{2h_1} > 0$, is compared to the objective value at the bound $\pi_A \geq \frac{ac-K-a\pi_I}{\beta_c}$. Together, Eqs. (4.12) and (4.13) describe the complete analytical solution to the conditional model of Eq. (4.10). While we now have $\pi_A^*(\pi_I)$ expressed as a linear function of π_I, there are three possible candidate solutions; which is the true solution to the conditional model depends on whether certain conditions on π_I are met. To solve the unconditional optimization problem of Eq. (4.11), we must therefore examine four distinct single-variable quadratic programs, each of which is constructed by substituting one of the possible candidate solutions $\pi_A^*(\pi_I)$ into the objective function of the conditional model, with the corresponding conditions required on π_I, as defined in Eqs. (4.12) and (4.13). We will denote each of these four programs as "A1", "A2", "B1", and "B2", where A and B respectively denote which of $h_3\pi_I + h_4 \leq 0$ or $h_3\pi_I + h_4 > 0$ holds, and 1 and 2 respectively denote whether the first or second case in the specification of $\pi_A^*(\pi_I)$ (i.e., in Eq. (4.12) or Eq. (4.13)) obtains. For example, Program A1,

$$\begin{array}{rrcl} z_{A1}^* = \max\limits_{\pi_I} & h_2\pi_I^2 + h_5\pi_I + h_6, & & \\ \text{s.t.} & h_3\pi_I + h_4 & \leq & 0, \\ & ac - K - a\pi_I & \leq & 0, \\ & \pi_I & \geq & 0, \\ & \pi_I & \leq & c, \end{array} \tag{4.14}$$

is constructed by substituting $\pi_A^*(\pi_I) = 0$ into the objective function of the conditional model from Eq. (4.10) and additionally constraining π_I with $h_3\pi_I + h_4 \leq 0$ and $ac - K - a\pi_I \leq 0$. The objective function is maximized by choosing π_I, where as always, $0 \leq \pi_I \leq c$ must also hold. We denote the optimal solution to Program A1 as z_{A1}^*, which is computationally treated as negative infinity if the program is infeasible. The remaining programs A2, B1, and B2 are constructed in an analogous manner. In Program A2, $\pi_A^*(\pi_I) = \frac{ac-K-a\pi_I}{\beta_c}$, yielding

$$
\begin{aligned}
z^*_{A2} = \max_{\pi_I} \quad & h_2\pi_I^2 + h_5\pi_I + h_1\left(\tfrac{ac-K-a\pi_I}{\beta_c}\right)^2 + (h_3\pi_I + h_4)\left(\tfrac{ac-K-a\pi_I}{\beta_c}\right) + h_6, \\
\text{s.t.} \quad & \begin{array}{rcl} h_3\pi_I + h_4 & \leq & 0, \\ ac - K - a\pi_I & \geq & 0, \\ \pi_I & \geq & 0, \\ \pi_I & \leq & c. \end{array}
\end{aligned}
\tag{4.15}
$$

Next, in Program B1, $\pi^*_A(\pi_I) = \frac{-h_3\pi_I - h_4}{2h_1}$, leading to

$$
\begin{aligned}
z^*_{B1} = \max_{\pi_I} \quad & h_2\pi_I^2 + h_5\pi_I + h_1\left(\tfrac{-h_3\pi_I-h_4}{2h_1}\right)^2 + (h_3\pi_I + h_4)\left(\tfrac{-h_3\pi_I-h_4}{2h_1}\right) + h_6, \\
\text{s.t.} \quad & \begin{array}{rcl} h_3\pi_I + h_4 & > & 0, \\ \frac{ac-K-a\pi_I}{\beta_c} & \leq & \frac{-h_3\pi_I-h_4}{2h_1}, \\ \pi_I & \geq & 0, \\ \pi_I & \leq & c. \end{array}
\end{aligned}
\tag{4.16}
$$

And finally, in Program B2, $\pi^*_A(\pi_I) = \frac{ac-K-a\pi_I}{\beta_c}$, yielding

$$
\begin{aligned}
z^*_{B2} = \max_{\pi_I} \quad & h_2\pi_I^2 + h_5\pi_I + h_1\left(\tfrac{ac-K-a\pi_I}{\beta_c}\right)^2 + (h_3\pi_I + h_4)\left(\tfrac{ac-K-a\pi_I}{\beta_c}\right) + h_6, \\
\text{s.t.} \quad & \begin{array}{rcl} h_3\pi_I + h_4 & > & 0, \\ \frac{ac-K-a\pi_I}{\beta_c} & \geq & \frac{-h_3\pi_I-h_4}{2h_1}, \\ \pi_I & \geq & 0, \\ \pi_I & \leq & c. \end{array}
\end{aligned}
\tag{4.17}
$$

In summary, we solve the unconditional problem of Eq. (4.11) by decomposing it into four distinct programs, solving each one, and comparing their objective values. That with the greatest objective value determines the solution (π^*_A, π^*_I) and the optimum z^*. Mathematically, the solution strategy rests on

$$
z^* = \max(z^*_{A1}, z^*_{A2}, z^*_{B1}, z^*_{B2}). \tag{4.18}
$$

Intuitively, each program explores a different one-dimensional subspace of the feasible region for (π_A, π_I), dramatically reducing the search space of the original model. For example, Program A1 explores the part of the feasible region where $\pi_A = 0$ and $0 \leq \pi_I \leq c$, Programs A2 and B2 explore the feasible region along the inducement threshold line, and Program B1 explores possible interior solutions. Indeed, if we determine that a program is infeasible, we guarantee that the unconditional solution does not lie within that exploration region. In Section 4.5, we illustrate this procedure when we apply our solution strategy to the BEV case study.

Most importantly, our solution strategy effectively circumvents the possible non-convexity of the QP in Eq. (4.8), thereby guaranteeing a global maximum. To see this, we examine the convexity of the four single-variable programs. First, Program A1 is a convex optimization problem since $h_2 < 0$ by assumption. Second, Programs A2 and B2 are convex if and only if $b - \beta_b > 0$, which is again true by assumption. Finally, Program B1 is convex if and only if $8\beta_c ab - 6\beta_b\beta_c a \geq \beta_b^2 a^2 + \beta_c^2$, which is the same condition required for convexity of the original model in Eq. (4.8). In practice, however, non-convexity of Program B1 does not carry the same troubling consequences as non-convexity of the original model. Indeed, suppose that Program B1 is non-convex, i.e., the objective function to be maximized is concave-up. Then, a global maximum must exist at either the lower or upper bound on π_A, and it therefore suffices to simply evaluate the objective function value at these bounds and choose the greater of the two. In Proposition 4.4, we summarize these findings that guarantee a global maximum with our solution strategy.

Proposition 4.4. *Programs A1, A2, and B2 are convex. Program B1 is convex if and only if* $8\beta_c ab - 6\beta_b\beta_c a \geq \beta_b^2 a^2 + \beta_c^2$*. If Program B1 is feasible but non-convex, then the solution is determined by evaluating the objective function at the lower and upper bounds on* π_A*, and choosing whichever of the* *two gives the greater objective value.*

Proof. See Appendix C.2.4.

In practice, it is straightforward to determine which programs are infeasible, in which case it is not even necessary to pass the program to a solver. For example, if $h_4 < 0$, then Programs B1 and B2 are infeasible, and only A1 and A2 need to be evaluated.

Because of (1) the reduced solution search space, (2) the ease with which infeasibility is established, (3) the ease with which single-variable QPs are solved, and (4) the guarantee of terminating with a global maximum even under non-convexity, we hypothesize that our solution strategy will outperform solving the original two-variable, possibly non-convex QP directly using an off-the-shelf solver. This hypothesis is tested in the next section, where we apply our model to a case study on technology policy for supporting the diffusion of BEVs.

4.5 Case study: battery electric vehicles

The timely decarbonization of the transport sector is one of the most challenging components of climate change mitigation, as the current performance and cost characteristics of batteries mean that electric vehicles are struggling to displace their gasoline-fueled counterparts. National, regional, and municipal governments have already implemented many policies to encourage adoption of BEVs. For example, California's Executive Order B-48-18 proposes an investment of \$9 million to deploy 250,000 EV charging points by 2025, the U.S. Department of Energy's Vehicle Technologies Office supports battery R&D funding, and the Government of Canada has allocated \$225 million for purchase incentives of up to $3750 per vehicle (IEA, 2019). While a number of empirical studies have found that, among other variables, consumer adoption subsidies and the availability of charging points have predictive power for EV adoption levels, there is no modeling framework that suggests how public funds should be optimally allocated between adoption subsidies and infrastructure investment subsidies. Indeed, Sierzchula et al. (2014) note that cost-effectiveness or cost-benefit analysis is needed to determine if such policies are actually efficient in a societal and economic sense. Here, we address this gap in the energy policy literature on supporting EV diffusion by parameterizing and applying our bilevel framework to a relevant real-world case study. We begin by explaining the parameterization, then analyze the case study results to derive insights for BEV incentive policies, and finally compare our solution strategy developed in Section 4.4 to solving the original, possibly non-convex QP using an off-the-shelf solver.

4.5.1 Parameterization

In this case study, the infrastructure-dependent technology under consideration is the battery electric vehicle (BEV) and the associated infrastructure is the Level II AC public charging point, the most common public charging technology at present. The geographic scope of our case study is the entirety of the United States, and so the policymaker is understood to make her decisions based on national costs and benefits.

The policymaker's objective function in Eq. (4.5) specifies that the benefit of the implemented technology policy is proportional to the number of BEV adopters it results in, as captured by the α parameter. In this parameterization, α represents the incremental benefit (due to reduced GHG emissions) when a BEV is purchased instead of a conventional internal combustion engine vehicle (ICEV). In Table 4.1, we calculate α as the social cost of carbon at \$50/tonne CO_2 multiplied by the difference in CO_2 emissions between the ICEV and BEV, over their lifetimes, assuming standard efficiencies, vehicle lifetimes, and annual vehicle miles traveled.[3] In this calculation, we include upstream electricity generation emissions for the BEV, based on the average carbon intensity of electricity generation in the U.S. Thus, in our parameterization, $\alpha = \$1549.44$; i.e., the social climate benefit generated by the adoption of one BEV instead of one ICEV is worth approximately \$1550. The number of innovator adopters, or those who will adopt the BEV technology even if there were neither an adoption subsidy nor infrastructure subsidy, is parameterized at 2.5% of the pool of potential adopters n, taken here to mean the approximate number of new light-duty vehicle (LDV) annual sales in the U.S. (approximately 17.2 million); i.e., $K = 431,856$. This slice of the pool of potential adopters is consistent with the Rogers (1962) adopter classification and has been used in other numerical analyses of electric vehicle adoption (e.g., see Priessner et al. (2018)). As a reference point, BEVs enjoyed approximately 2% market share in the U.S. in 2018 (EVAdoption, 2019).

Since our model depicts only one type of infrastructure, we assume that the charging points are of the Level II AC public charger type, which typically have a power rating of 3.6 kW. Schroeder and Traber (2012) provide a rich accounting of the economics of electric vehicle chargers, from which we have arrived at a standard cost of approximately \$5500 per charger[4], which is typical

[3] While the scope of our case study is at the U.S. national level, the social cost of carbon used to parameterize α is a global estimate.

[4] Strictly speaking, the \$5500 cost per charger is a market *price*, rather than a true cost. Due to the relatively young market for charging points and the dearth of data, we have not

across a variety of sources. Indeed, Level II AC chargers are likely to be the prevailing technology for charging point infrastructure over the next decade (IEA, 2019).

To determine potential adopters' sensitivity to adoption subsidies (β_c) and the availability of charging points (β_b), we use the linear regression results obtained by Sierzchula et al. (2014). Their study examines the relationship between BEV market share and a number of socioeconomic factors expected to be influential determinants of BEV market share in 30 national markets in 2012, including financial incentives (registration and circulation subsidies); the number of charging points corrected for population; national differences in environmentalism; gasoline, diesel, and electricity prices; urban density; and several others. The authors conclude that financial incentives and availability of charging infrastructure were the only statistically significant predictors of BEV market share at the $p < 0.05$ level.[5] The model specification is log-linear, in which the dependent variable, BEV market share, is log-transformed; the independent variables are linearly specified. They find that a $1000 increase in financial incentives would cause a country's BEV market share to increase by 0.06%, and each additional charging station per 100,000 residents would increase BEV market share by 0.12%. In Table 4.1, we use these regression coefficients to calculate the adoption parameters β_c and β_b, which require us to also define the population size N. We find that $\beta_c = 10.36$ and $\beta_b = 5.92$. In other words, an additional dollar of adoption subsidy promised to potential

been able to find reliable estimates for the latter.

[5]The regression has an R^2 of 0.792 and the data point for the United States is not an outlier. Further, in a model sensitivity test, the authors remove both the financial incentives and the availability of charging points independent variables and find that the model loses most of its explanatory power.

adopters results in approximately 10 additional adopters and an additional charging point results in approximately 6 additional adopters.

Finally, it remains to parameterize a and b. Parameters a and b appear in the inverse demand curve for charging points, $p(y) = \frac{\beta_c \pi_A + K}{a} - \frac{b - \beta_b}{a} y$, and their effects can be intuited through it. For example, an additional charging point built will decrease the market price by $\frac{b-\beta_b}{a}$, the slope of the demand curve. Additionally, the price intercept if $\pi_A = 0$ is $\frac{K}{a}$. For the same reason that we are unable to find reliable estimates for the true cost of charging points, parameterizing this demand function, and thus obtaining precise estimates for a and b, is difficult. To generate insights for the BEV case study, and to explore possible non-convexity, we fix $a = 100$ and explore the optimal solution for $b = 10$ and $b = 50$. Thus, an additional charging point will lower the market price by $\frac{b-\beta_b}{a} = \$0.04$ in the case $b = 10$ or by \$0.44 in the case $b = 50$, reflecting different market conditions for the infrastructure firm. In the following section, we explore the sensitivity of the optimal solution for a variety of b, K, and social cost of carbon (SCC) estimates. Naturally, using our bilevel model to inform real technology policy decision making is parameterization-dependent, and many of the parameter estimates given in Table 4.1 could be argued. In that sense, this case study is meant to demonstrate and complement the core contribution of this chapter: a stylized cost-benefit model of infrastructure-dependent technology adoption and supporting policies. While it is beyond the scope of this chapter, an in-depth study estimating the model's parameters and performing broad sensitivity analyses would certainly be a valuable step toward using our analytical model to make precise policy recommendations.

	Parameter	Value	Data Source	Notes
[1]	Social cost of carbon	50 [$/tonne CO_2]	RFF (2019)	Global SCC at 3% discount rate. $7 for US Domestic.
[2]	CO_2 intensity of electricity generation	0.00044844124 [tonne/kWh]	EIA (2020)	Based on US Electricity Generation in 2018
[3]	EV electricity consumption	0.3 [kWh/mile]	DOE (2020)	Typical efficiency - Nissan Leaf, Volkswagen E-Golf, and Tesla Model 3
[4]	CO_2 intensity of ICEV	0.000404 [tonne/mile]	EPA (2018)	
[5]	Annual VMT	11,500 [miles]	EPA (2018)	
[6]	Lifetime of vehicle	10 [years]		
	$\boldsymbol{\alpha}$	$1549.44 [$/adopter]		Calculated: [1]*([4]*[5]*[6] - [2]*[3]*[5]*[6])
[7]	Charging point cost	1522 [$/kW]	Schroeder and Traber (2012)	For a Level II AC Public charger
[8]	Power rating per charging point	3.6 [kW/Charging Point]	Schroeder and Traber (2012); IEA (2019)	
	$\boldsymbol{c}$	5479.2 [$/charging point]		Calculated: [7]*[8]
[9]	Market size (n)	17,274,250 [LDVs]	MarkLines (2019)	2018 U.S. Sales Volume of passenger, pickup, and SUV vehicles
[10]	Innovator Adopters as % of market size	2.5%	Priessner et al. (2018), Rogers (1962)	In 2018, U.S. BEV market share was 1.95% (EVAdoption, 2019)
	$\boldsymbol{K}$	431,856 [Adopters]		Calculated: [9]*[10]
	$\boldsymbol{\beta_c}$	10.36 [Adopters]	Sierzchula et al. (2014)	Calculated: [9]*.0006/1000
[11]	Population size (N)	328,239,523	U.S. Census Bureau (2019)	
	$\boldsymbol{\beta_b}$	5.92 [Adopters]	Sierzchula et al. (2014)	Calculated: (.12*[9]*100,000)/(100*[11])
	$\boldsymbol{a}$	100		
	$\boldsymbol{b}$	50		Varied in analysis

Table 4.1. Table of parameters for the case study on BEV diffusion. The data in numbered rows are used in calculations to estimate the model's parameters, given in bold.

4.5.2 Case study solutions

In addition to presenting the solution to the BEV case study with the unique parameterization given in Table 4.1, we also explore several other parameterizations by varying those parameters which we believe to be subject to the most uncertainty. First, we consider $b = 10$ and $b = 50$ as described above to explore not only different market conditions for the infrastructure firm, but also solution times to optimality, since for each of the instances solved with $b = 10$, the optimization problem is non-convex, and for each of the instances solved with $b = 50$, the optimization problem is convex. Second, we consider three levels of K (1000, 431,856, and 1,000,000), for which it is difficult to obtain robust estimates. And third, we consider two SCC estimates, \$50/tonne and \$75/tonne, which respectively assume 3% and 2.5% discount rates (RFF, 2019). In Table 4.2, we present the optimal solutions for the 12 cases generated by varying the parameters discussed above. For each set (b, K, SCC), we report the optimal subsidies for adoption (π_A^*) and infrastructure investment (π_I^*), the optimal objective value z^*, the level of infrastructure provision $y^*(\pi_A, \pi_I)$, and the number of adopters $x(\pi_A, y)$.

We begin our discussion with the case $b = 50$, and in particular the solution for the case study parameterization [9], which is in bold in Table 4.2. Our model's technology policy recommendation is to provide zero adoption subsidy and a \$5167 infrastructure subsidy to the firm, reducing its per-unit production cost to \$312. Approximately 4544 charging points are built, leading to 458,757 BEV adopters. That is, the technology policy generates 26,901 additional adopters beyond those innovator adopters K, with net positive social benefits worth approximately \$687 million. Indeed, in this case, the resolution of the chicken-and-egg problem is that the policymaker supports infrastructure

Case	b	K	SCC	π_A^*	π_I^*	z^*	$y^*(\pi_A, \pi_I)$	$x(\pi_A, y)$
[1]	10	1000	\$50	\$532	\$5479	\$7,059,205	798	11,233
[2]	10	1000	\$75	\$919	\$5479	\$18,444,257	1290	18,158
[3]	10	431,856	\$50	\$0	\$5167	\$865,803,445	49,093	722,489
[4]	10	431,856	\$75	\$0	\$5479	\$1,441,898,846	52,924	745,163
[5]	10	1,000,000	\$50	\$0	\$2326	\$2,123,922,137	83,906	1,496,724
[6]	10	1,000,000	\$75	\$0	\$4619	\$3,347,907,411	112,009	1,663,091
[7]	50	1000	\$50	\$726	–	\$7,016,821	0	8526
[8]	50	1000	\$75	\$1085	\$5479	\$15,425,825	139	13,059
[9]	**50**	**431,856**	**\$50**	**\$0**	**\$5167**	**\$687,337,949**	**4544**	**458,757**
[10]	50	431,856	\$75	\$0	\$5479	\$1,044,260,785	4899	460,855
[11]	50	1,000,000	\$50	\$0	\$2326	\$1,602,612,449	7766	1,045,976
[12]	50	1,000,000	\$75	\$0	\$4619	\$2,418,915,470	10,367	1,061,375

Table 4.2. Optimal solutions for varied b, K, and SCC (which affects α) parameters. The bold case [9] is the solution to the parameterization given in Table 4.1. A dash in the π_I^* column reflects the idea that if $y^*(\pi_A, \pi_I) = 0$, decision variable π_I has no bearing on the optimal solution.

provision but not adoption. We hypothesize that no adoption subsidy is provided because the large number of innovator adopters implies that the total adoption policy cost would ex-ante exceed the benefits. Instead, policy funds are more valuable if directed toward the infrastructure firm. Because $\pi_A^* = 0$, the policymaker is not "double-charged" for the infrastructure policy, for otherwise she would pay the direct cost $y\pi_I$ *and* the indirect cost $\beta_b y \pi_A$, since y increases with π_I and π_A. If the SCC increases to \$75/tonne, as in case [10], this effect is only amplified: more benefits are on the table for the same number of adopters, and so the policymaker incurs a greater infrastructure policy cost to generate additional adopters, effectively subsidizing the entire investment cost of infrastructure provision. This "double-charging" effect is so strong that it is not until the SCC reaches \$1350 that the solution actually changes, and it becomes optimal for the policymaker to activate adoption subsidies in addition to the infrastructure subsidy. Figure 4.3 illustrates the magnitude of this "double-charging" effect. Indeed, while the policymaker's objective function value remains relatively flat along the π_I dimension, increases in π_A lead to this double-charging effect, rapidly decreasing the objective value. For example, in Figure 4.3, feasible policy allocations on the red line are within 25% of optimality, indicating a very steep objective function in the π_A dimension. As a matter of technology policy design, suboptimal policy allocations can carry considerable consequences. Intuitively, in this case, the large number of innovator adopters K means any positive adoption subsidy π_A induces significant costs without corresponding benefits. In general, we attribute this steepness to the linearly specified functional forms.

In cases [11] and [12], the number of innovator adopters K is considerably larger at 1 million, or about 6% of the pool of potential adopters. Here, the infrastructure subsidy is smaller because the higher number of innovator adopters drives up infrastructure provision, which increases the total infrastructure policy cost. With respect to the SCC, the same double-charging effect holds. On the other hand, in cases [7] and [8], when K is very low, the firm faces considerably difficult market conditions: prices drop steeply and it cannot count on innovator adopters alone to constitute the demand for infrastructure provision. In case [7], a modest adoption subsidy is provided, but the firm does not invest in any infrastructure. Between cases [7] and [8], as the SCC increases, so does the policymaker's motivation to raise the number of adopters. First, this is achieved by increasing the adoption subsidy. However, the firm's optimal response depends on the adoption subsidy, and

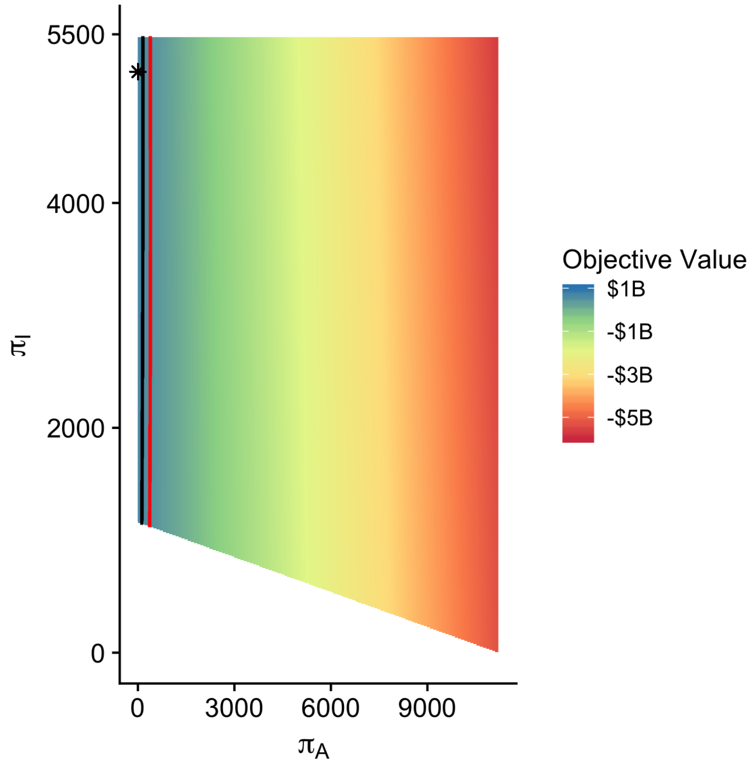

Figure 4.3. Contour map of the policymaker's feasible region in case [9]. The optimal solution is denoted by the asterisk at $(\pi_A, \pi_I) = (0{,}5167)$, and the black and red lines are optimality thresholds, denoting solutions within 10% and 25% of optimality, respectively.

when it becomes high enough at an SCC of $56/tonne, the firm supplies a positive quantity of infrastructure. A noteworthy phenomenon occurs between SCC values of $55/tonne to $56/tonne: the adoption subsidy increases and reaches a maximum at $55/tonne, where the infrastructure provision is still zero. At $56/tonne, the adoption subsidy falls from its $55/tonne level and infrastructure provision becomes positive. Thereafter, as the SCC increases, so too do the adoption subsidy and infrastructure provision. Intuitively, the policymaker knows when the firm will supply positive infrastructure. At this point, she can now completely incentivize the firm and further increase net benefits of the policy as long as she slightly reduces her adoption subsidy.

For the case $b = 10$, we uncover similar insights. First, a large number of innovator adopters implies that technology policy should focus on incentivizing infrastructure provision, not adoption directly. Once the infrastructure subsidy reaches its limit, and further policy is spurred by a higher SCC, the adoption subsidy increases. In cases [1] and [2], the double-charging threshold has already been passed, and the adoption subsidy is positive and increases with the SCC. With higher K, we again see that a larger and larger SCC is necessary for it to be optimal to choose a positive adoption subsidy.

From the cases above, we can summarize the insights we glean on the chicken-and-egg problem. First, a large number of innovator adopters makes it suboptimal to offer an adoption subsidy; public funds are better spent supporting the associated infrastructure investment. Second, while public funds are better spent supporting the associated infrastructure, higher marginal social benefit with respect to the number of adopters (e.g., due to a higher SCC estimate) should eventually induce the policymaker to additionally provide an adoption subsidy. And third, under a combination of a small number of innovator adopters and unfavorable market conditions for the infrastructure firm, the policymaker should exclusively provide adoption subsidies. As the marginal social benefit for each additional adopter increases (as is the case with an increasing SCC), the policymaker should raise her adoption subsidy until it becomes optimal for the firm to invest positively in infrastructure, at which point the policymaker "corrects" her choice by lowering the adoption subsidy and applying a positive infrastructure subsidy.

4.5.3 Comparison of solution methods

In this subsection, we demonstrate the application of the custom solution strategy developed in Section 4.4 to our BEV case study, and compare its performance to an off-the-shelf solver applied directly to the original, possibly non-convex QP reformulation from Eq. (4.8).

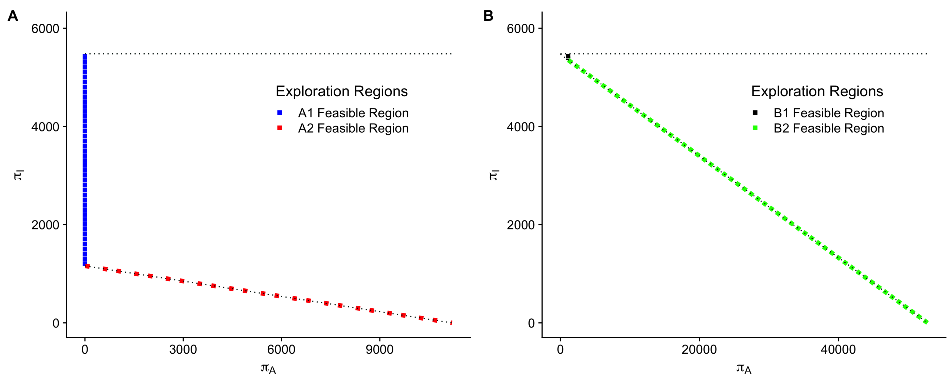

Figure 4.4. Illustration of the solution strategy. Panel A is an instance of case [9] and Panel B is an instance of case [8]. The light, dotted black lines indicate the bounds of the feasible regions.

We begin with an illustration of the the solution strategy developed in Section 4.4, which reduces the solution search space of the quadratic model and circumvents possible non-convexity by solving the four single-variable QPs called A1, A2, B1, and B2. In Figure 4.4, we visualize the one-dimensional subsets of the feasible region that are explored by the decomposition programs. Figure 4.4A is an instance of case [9] and Figure 4.4B is an instance of case [8]. In case [9], both the B1 and B2 programs are infeasible, and so the solution strategy only explores the cases $\pi_A = 0, c - \frac{K}{a} \leq \pi_I \leq c$ and $\pi_A = \frac{ac-K-a\pi_I}{\beta_c}, 0 \leq \pi_I \leq c - \frac{K}{a}$. In other words, the solution strategy explores only where $\pi_A = 0$ or $y^*(\pi_A, \pi_I) = 0$. For case [8], both the A1 and A2 programs are infeasible,

Case	b	K	SCC	Convex	Off-The-Shelf Solver (s)	Custom Solution Strategy (s)
[1]	10	1000	\$50	No	0.04717445	**0.01641188**
[2]	10	1000	\$75	No	0.03520974	**0.01276198**
[3]	10	431,856	\$50	No	0.02907454	**0.02420106**
[4]	10	431,856	\$75	No	0.02922226	**0.02431191**
[5]	10	1,000,000	\$50	No	0.01318080	**0.01197627**
[6]	10	1,000,000	\$75	No	0.01348885	**0.01190357**
[7]	50	1000	\$50	Yes	0.03580216	**0.02509426**
[8]	50	1000	\$75	Yes	0.02962216	**0.02388696**
[9]	50	431,856	\$50	Yes	0.03180345	**0.02417662**
[10]	50	431,856	\$75	Yes	0.03032642	**0.02386467**
[11]	50	1,000,000	\$50	Yes	0.01334619	**0.01185480**
[12]	50	1,000,000	\$75	Yes	0.01322027	**0.01185028**

Table 4.3. Performance comparison of solution strategies for varied b, K, and SCC parameters. Solution times (in seconds) are averages over 1000 trials.

and the solution strategy searches only along the inducement threshold line and interior solutions from this line to the upper bound $\pi_I = c$.

Practically, we would like to understand whether our custom solution strategy outperforms applying an off-the-shelf solver directly to the original, possibly non-convex QP. As a comparison, we test our strategy against Gurobi 9.0's quadratic programming solver. If the resulting model is indeed non-convex, then Gurobi applies a branch-and-bound technique to arrive at global optimality; otherwise, a barrier method is used. It turns out that Gurobi and our custom strategy return the same optimal solutions for all parameterizations, so the relevant outcomes for the comparison are their respective solution times required to determine the global maximum.

In Table 4.3, we list average solution times (over 1000 trials) for the 12 cases defined above and report whether or not the instance is convex. The solution times (in seconds) are reported in the last two columns, and the time for the faster method is displayed in bold. We see that our custom solution strategy outperforms Gurobi for all the convex and non-convex instances. This brief comparison suggests that our decomposition strategy is a compelling alternative to directly solving the two-variable QP. Our technology policy problem in this chapter is very small, so the choice between these two methods is more of an intellectual exercise than a practical necessity. Nevertheless, the performance gains from using our solution approach could be important for larger problems with a similar structure.

4.6 Conclusions

This chapter makes fundamental advances in modeling and understanding how a policymaker should design incentives to overcome the chicken-and-egg problem of infrastructure-dependent technology diffusion. While this chapter is primarily a theoretical contribution that develops a stylized model capable of yielding analytical insights, the practical importance of understanding these processes is tremendous. For instance, research suggests that the looming threat of climate change may be mitigated by realizing the widespread adoption of clean technologies in the transportation and electricity sectors. The BEV, which requires a system of charging infrastructure to compete with ICEVs, and wind and solar PV generation, which require substantial energy storage to displace fossil fuel plants on a massive scale, are touted as possible solutions to climate change. Therefore, a policymaker must consider not only the core technology, but also the associated system of infrastructure required to support it and make it attractive to potential adopters.

In this chapter, we have presented a stylized model of technology policy decision making from the perspective of a policymaker who seeks to stimulate the market penetration of an infrastructure-dependent technology. Our model is a bilevel optimization problem in which a policymaker (leader) maximizes net social benefits by setting the levels of two incentives: a subsidy for a profit-maximizing firm (follower) to invest in infrastructure that raises the benefit of adoption to consumers, and a direct subsidy for consumers to adopt the technology. We have analytically derived the firm's optimal infrastructure investment response to the upper-level policy decisions, and shown that the bilevel model is equivalent to a quadratic program. To bypass non-convexity, we developed a custom solution strategy based on decomposition, and found that it performs better than directly applying an off-the-shelf solver to the potentially non-convex problem. Finally, we applied our bilevel framework to a case study on the diffusion of BEVs and obtained insights into how a policymaker should allocate resources to charging infrastructure and vehicle incentives. The case study results certainly suggest that U.S. BEV incentives would likely be more effective if some public funding were shifted from vehicle subsidies to charging infrastructure subsidies, although this conclusion cannot be asserted with complete confidence given the lack of data on the market for use of charging points, among other factors.

As with any theoretical modeling effort structured to yield analytical insights, we had to make some simplifying assumptions in order to preserve tractability. These limitations were summarized above at the end of Section 4.3.3. Despite these simplifications, we have contributed a fresh model of infrastructure-dependent technology adoption and the chicken-and-egg problem to the operations research literature, and demonstrated the benefits of using a custom solution strategy to solve it. The model itself is our most significant contribution.

Future research should attempt to extend our model in several valuable directions. The deterministic model could be turned into a stochastic one to capture uncertainty on several levels. In reality, the policymaker does not generally know the parameters of the infrastructure firm's problem with certainty, and the adoption level resulting from adoption subsidy and infrastructure provision decisions depends on consumer behavior and other factors which are impossible to predict. Similarly, our static model could be extended to multiple time periods to investigate whether the optimal subsidy portfolio varies over time to emphasize different instruments at different times. Instead of having just one infrastructure firm, the lower level could have multiple infrastructure firms competing with one another, which could be handled through a mathematical program with equilibrium constraints (MPEC). To address another noted limitation of the model, some of the functions which we implicitly assume are linear (e.g., the policymaker's objective, the adoption function) could be generalized to allow for more empirically realistic forms. However, all of these extensions would add considerable complexity to the framework, thus likely coming at the expense of analytical tractability and the ability to parameterize case studies using regression results from the literature.

4.7 Acknowledgments and notes

Benjamin Leibowicz contributed to the conceptualization of the topic. We thank seminar audiences at the INFORMS Annual Meeting 2019 for helpful

comments and suggestions. A version of this chapter is under review at *European Journal of Operational Research*.

Chapter 5

Conclusion

The goal of this dissertation is to advance the operations research modeling of technology transitions and the role of policy support. Through a variety of powerful operations research methodologies and relevant case studies, the individual projects in this dissertation offer novel models of technology transitions and insights into real-world technology policy.

The three projects of this dissertation employ distinct operations research methods to model technology transitions and the role of policy support. Chapter 2 describes the development of an urban-scale energy system optimization model. This work prompted a number of research questions concerning technology transitions that motivated the more fundamental, stylized models developed in Chapter 3. And, finally, in Chapter 4, our focus on technology transition models narrows with the development of a stylized model of optimal technology policy decision making for infrastructure-dependent technologies. For each modeling development, we also presented a case study to illustrate how our models could be used in real-world technology policy decision making.

In this concluding chapter, we first summarize our key findings and contributions, then elaborate on future research directions to advance the understanding of technology transitions and the role of policy support.

5.1 Summary of contributions and findings

Chapter 2 addresses the growing importance of cities in climate change mitigation with the development of an energy system optimization model for urban-scale decarbonization. Our optimization model determines the least-cost power and transportation technology pathways to achieve a policy goal of net-zero greenhouse-gas emissions and is used to analyze the Community Climate Plan adopted by Austin, Texas. Our approach to energy system optimization is novel in that we are able to capture the synergies between power and transportation. The power and transportation sectors are the two largest GHG emitters in the U.S., accounting for 28% and 29% of total emissions, respectively (EPA, 2017b), and evidence suggests that these shares are even higher in urban areas. Any serious effort to decarbonize cities will therefore require monumental changes in how we generate electricity and travel from place to place. At present, transportation and power are largely decoupled, at least in the U.S. Petroleum products dominate the fuel mix of the former, but have been almost completely phased out of the latter. This situation is likely to change in the future as transportation shifts to alternative fuels that are more closely linked to the power sector, especially under climate policies (Anandarajah et al., 2013; Bosetti and Longden, 2013; Edelenbosch et al., 2017; Pietzcker et al., 2014). Amid this trend, powerful synergies will emerge whereby mitigation activities in power and transportation mutually enhance one another. We design our model to leverage these synergies while optimizing decarbonization pathways.

We find that the ACCP increases net present power and transportation costs by 2.7% relative to business-as-usual. This economic impact is not trivial, but it does demonstrate that even the particularly ambitious net-zero emissions by 2050 goal can be achieved at modest cost. The optimal decarbonization pathway consists of two sequential stages: the power sector is decarbonized first, then the focus shifts to transportation. The ACCP hastens the elimination of coal from the power sector, initially through substitution by natural gas, but increasingly via the expansion of renewables. Solar PV actually comprises a majority of the 2050 generation mix even in the absence of climate policy, based on optimistic cost projections alone. The primary long-run impact of the ACCP on electricity is the replacement of natural gas with wind, which is an effective complement to solar PV under high renewable penetration due to their contrasting temporal profiles (wind at night, solar PV during the day). Once electricity decarbonizes, private transportation transitions to electric vehicles, which are less costly in these later years. Capital cost differentials between carbon-free and conventional options are more extreme in public transportation, which is therefore insensitive to the policy context, even under a scenario of significant modal shift from private to public transportation. Intelligent and coordinated scheduling of battery electricity storage and electric vehicle charging play important roles in the low-carbon transition. Battery storage charges during the daytime when solar PV is abundant and discharges at night when solar PV is unavailable. Optimal electric vehicle charging also occurs during the daytime to align with solar PV availability, which implies that making charging infrastructure available at workplaces would provide substantial system-wide value. Our model does not select V2G or hydrogen technologies in its optimal decarbonization pathways.

Energy system optimization models, while case- and parameterization-specific, remain valuable tools for designing intelligent technology policy. For example, our transformation pathways offered what could be promising transition fuels and provided insights into how intermittent renewable energy sources could be managed with energy storage technologies and synergistic electric vehicle charging schedules. By design and due to methodological limitations, our optimization framework does not capture other drivers of adoption besides cost considerations that arise from complex phenomena that exist in technology transitions. Indeed, while an energy system optimization model assumes that a technology transition will occur as long as a new technology becomes cost-effective, we know from empirical observations that there are a number of market failures that can hinder the diffusion of a technology even after it becomes economically competitive.

Addressing this issue required taking a step back and examining the first principles behind the processes of technology adoption and diffusion that drive technology transitions. In Chapter 3, we built on earlier theoretical operations research and economic models of technology adoption and diffusion to incorporate a policy decision maker. We determined that classic Markov stochastic processes were strong candidates for modeling a technology transition, with states representing stages of the diffusion process and a transition probability matrix engendering the uncertainty in success of the technology transition. Furthermore, decision making capabilities within the stochastic process could simulate policy intervention: policy intervention could map to a different transition probability matrix.

The first model is a Markov reward process (MRP) that represents policy interventions with one-time, upfront costs, while the second model is a Markov decision process (MDP) that describes policy interventions with recurring costs. The distinction is important and applies to different policy instruments. For example, R&D investment which permanently enhances the performance of a technology is well aligned with the persistent effect of the one-time investment in the MRP, whereas an adoption subsidy during a particular phase of the technology life cycle corresponds better to the recurrent cost accounting of the MDP. We derived analytical expressions for the willingness to pay (WTP) for policy interventions that improve the probabilities of the technology diffusion or development process advancing at various stages. We then analytically established key similarities and differences between the two models. Next, we numerically solved the most general MDP model to explore how the optimal technology policy portfolio varies over the input parameter space. Finally, we applied the MDP model to a case study on the development of lithium-ion batteries for electric vehicles, based on expert elicitations.

In terms of the specific results we obtained, the MRP and MDP models demonstrate some intuitive similarities. WTPs vary linearly with the rewards. They always increase with respect to the reward for being in the complete diffusion stage, but the WTP for policy intervention in the intermediate stage can decrease with the reward obtained in this stage since this reward makes completing the diffusion process less urgent. As the status-quo probability of the diffusion process advancing from a stage declines toward zero, the WTP for policy targeting this stage increases more and more steeply.

The possibility of regressing from the intermediate stage back to the initial stage has a substantial impact on the behaviors of both models, and carries important policy implications. In general, this possibility makes policy intervention less valuable in the initial stage but more valuable in the intermediate stage. With a danger of regressing from the intermediate stage back to the initial stage, the policymaker has a higher WTP to raise the probability that the diffusion process will advance from the intermediate stage to the complete diffusion stage. The numerical results reveal that the presence of the regressive transition in the MDP model makes policy intervention in the intermediate stage an important complement to earlier intervention in the initial stage. Without the former, the latter could incur policy costs repeatedly as the process makes it to the intermediate stage only to return to where it began. In fact, under certain circumstances, the policymaker would even be willing to pay for an intervention that actually reduces the probability of advancing from the intermediate stage to the complete diffusion stage if it comes with a sufficiently large reduction in the probability of regressing back to the initial stage. The possibility of regressing is also a necessary condition for all of the non-monotonic behaviors we uncovered.

The structural properties of the MRP and MDP models exhibit a few notable differences that suggest how policymakers ought to think differently about technology policy interventions with one-time versus recurring costs. The most striking difference is that, as the enhanced transition probabilities that intervention would purchase improve further, the resulting increases in WTP are subject to diminishing returns in the MRP, but are subject to constant returns in the MDP. The added value of incremental increases in the probabilities of advancing do not diminish in the MDP because the desire to avoid incurring policy costs repeatedly is an additional motivation to move the diffusion process forward. The same reasoning explains why the MDP is more powerfully affected by the possibility of a regressive transition than the MRP is.

Naturally, the Markov models are highly theoretical. While they generate analytical insights into whether technology policy intervention produces net benefits, and whether earlier or later stage intervention is superior, they do not explicitly represent any actual policy instrument. In other words, the relationship between policy expenditure and transition probability is a "black box." In Chapter 4, however, we do explicitly model infrastructure service and adoption subsidies, which work to stimulate adoption of an infrastructure-dependent technology from the supply and demand sides, respectively. Many technologies in energy, transportation, and telecommunications require large infrastructure systems to deliver benefits to adopters and society. Policymakers seeking to promote the diffusion of infrastructure-dependent technologies are often confronted with the chicken-and-egg problem: consumers are reluctant to adopt the technology without adequate infrastructure available, and firms are reluctant to invest in infrastructure without a sufficient number of adopters. This chicken-and-egg problem can hinder the diffusion of new technologies and prolong the timeframe over which existing technological systems remain locked-in. We formulated a stylized model of technology policy decision making from the perspective of a policymaker who seeks to stimulate the market penetration of an infrastructure-dependent technology in order to overcome the chicken-and-egg problem. Our model is a bilevel optimization problem in which a policymaker (leader) maximizes net social benefits by setting the levels of two incentives: a subsidy for a profit-maximizing firm (follower) to invest in infrastructure that raises the benefit of adoption to consumers, and a direct subsidy for consumers to adopt the technology. We analytically derived the firm's optimal infrastructure investment response to the upper-level policy decisions, and showed that the bilevel model is equivalent to a quadratic program. To bypass non-convexity, we developed a custom solution strategy based on decomposition, and found that it performs better than directly applying an off-the-shelf solver to the potentially non-convex problem. Finally, we presented a case study on the diffusion of battery electric vehicles and obtained insights into how a policymaker should allocate resources to charging infrastructure and vehicle incentives.

While this project is primarily a theoretical contribution that developed a stylized model capable of yielding analytical insights, the practical importance of understanding these processes is tremendous. For instance, research suggests that the looming threat of climate change may be mitigated by realizing the widespread adoption of clean technologies in the transportation and electricity sectors. The BEV, which requires a system of charging infrastructure to compete with ICEVs, and wind and solar PV generation, which require substantial energy storage to displace fossil fuel plants on a massive scale, are touted as possible solutions to climate change. Therefore, a policymaker must consider not only the core technology, but also the associated system of infrastructure required to support it and make it attractive to potential adopters.

In fact, our case study generated a number of insights for real-world technology policy for battery electric vehicles. First, a large number of innovator adopters makes it suboptimal to offer an adoption subsidy; public funds are better spent supporting the associated infrastructure investment. Second, while public funds are better spent supporting the associated infrastructure, higher marginal social benefit with respect to the number of adopters (e.g., due to a higher SCC estimate) should eventually induce the policymaker to additionally provide an adoption subsidy. And third, under a combination of a small number of innovator adopters and unfavorable market conditions for the infrastructure firm, the policymaker should exclusively provide adoption subsidies. As the marginal social benefit for each additional adopter increases (as is the case with an increasing SCC), the policymaker should raise her adoption subsidy until it becomes optimal for the firm to invest positively in infrastructure, at which point the policymaker "corrects" her choice by lowering the adoption subsidy and applying a positive infrastructure subsidy.

For the remainder of this chapter, we discuss the implications of this dissertation's work and describe future research directions.

5.2 Future research directions

The research directions offered in the individual chapters are valuable extensions that deserve attention: they would address modeling assumptions and limitations to develop more parsimonious and realistic models of technology transitions. However, in this chapter, we describe what ought to be a new paradigm in modeling technology transitions.

In Chapter 1, we described the history of technology transition research, which can be delineated into two research traditions – the operations research and economics tradition and the sociology of technology tradition. The former builds mathematical models of technology adoption and diffusion, while the latter develops fundamentally qualitative frameworks that identify how socio-technical transitions occur. We believe that future research must exploit the insights and organization of the latter to advance the former. Uniting the two streams of research in this way is certainly an ambitious task, but we believe that operations research methodologies offer useful modeling frameworks and tools for advancing the quantitative analysis of technology diffusion processes and technology policy decision making.

The multi-level perspective of technology transitions purports that the socio-technical system can be represented by three interacting levels: niches, socio-technical regimes, and an exogenous socio-technical landscape (Geels, 2002, 2004). The socio-technical regime is characterized by path-dependence and lock-in, which are represented in three constituent parts: the socio-technical system, actors, and rules. Systemic developments in the socio-technical landscape are beyond the influence of the regime and are slow to change. When the existing socio-technical regime is replaced by another, a technology transition occurs. Radical innovations, i.e., innovations which are incompatible with the existing socio-technical regime, incubate in niches. In these niches, innovations enjoy protection from market selection and allow the opportunity for the innovation to deviate from the "rules" of the regime, experiment, and learn. Simultaneous pressure on the regime at the landscape level helps induce a technology transition. In addition to the MLP, other conceptual approaches for understanding technology transitions include ecological modernization theory, sociology and social practice theory, and political ecology, each focusing on different themes with different units of analyses (Sovacool, 2016). Such qualitative frameworks offer value to quantitative modeling efforts by systematizing and organizing a way of thinking broadly about technology transitions.

Nevertheless, some researchers may balk at the idea that such purely qualitative work has any ability to inform technology policy or contribute to our understanding of technology transitions. And without a corresponding, rigorous mathematical treatment and reliable data, their reservations would be well-founded. However, that does not mean that these frameworks, essentially an organization or ecology of perceived phenomena, are useless. To combine the two would be an innovative and daunting project, but it can shed light on some key research questions and decision making problems that previous quantitative modeling work has not adequately addressed.

Seto et al. (2016) identify three types of carbon lock-in: 1) infrastructural and technological; 2) institutional; and 3) behavioral.[1] When folded in to a qualitative framework like the MLP, these lock-in types suggest the mechanisms by which complex and protracted technology transitions can occur. As a starting point, a policymaker should therefore target those mechanisms. However, constructing quantitative models of these lock-ins – and their interactions – will be challenging. In the sections below, we specifically identify several research directions that may begin to chip away at this modeling monolith.

5.2.1 Identification of niches

In the MLP framework, it is hypothesized that technological innovations incubate in niches, or relatively isolated market segments, where they may gain enough traction to pose a threat to or to apply substantial pressure on the locked-in incumbent socio-technical regime (Geels, 2019; Kemp et al., 1998). Future research could address this hypothesis. Specifically, we would like to understand how a policymaker can identify an appropriate niche, how she can support the technology within that niche, and how that support reverberates throughout the entire socio-technical system. Take, for example, the case of battery electric vehicles. There are a number of candidate niches where adoption of electric vehicles may be swifter and policy support more effective, than in the entire market segment of personal land-based transportation. These include shared autonomous vehicle fleets, public transportation fleets, and commercial shipping and delivery fleets. Within these niches, we may hypothesize that several barriers to adoption are eliminated or at least diminished.

[1] We believe this typology is applicable to *all* socio-technical systems, not just those responsible for carbon emissions.

For example, unlike in private vehicle fleets, battery charging times and range anxiety are less substantive issues, since coordinated fleets are not subject to individuals' preferences and so can be centrally planned. Infrastructure investments can be handled at large scales and in the context of financial business decisions. Indeed, charging schedules can be optimized around idle times in the case of shared autonomous vehicles or loading and unloading times in the case of shipping operations. Furthermore, the most significant barrier to adoption – behavioral and cultural norms – largely disappear as well. The issue of directly influencing individuals' habit-formed behavior and cultural proclivities is thus circumvented. And, finally, since the ultimate goal is to stimulate a technology transition, i.e., destabilize the incumbent socio-technical regime, a policymaker should like to understand how this niche support reverberates throughout the system. In other words, is policy support for technologies in niches effective? Economies of scale and learning-by-doing may emerge from the niche and make personal electric vehicles cost competitive and comparable in performance to incumbent internal combustion vehicles; behaviors and cultural norms may change as consumers gain confidence in their performance and reliability; and charging infrastructure may be more readily available for immediate consumer use. Identifying such a suitable niche, deciding on the type and level of policy support, and modeling how these decisions affect technological change outside of the protected niches is an optimization problem amenable to operations research methodologies. Furthermore, such a policy strategy could be compared to traditional policy instruments that do not directly target niches, thereby generating insights into real-world technology policy.

5.2.2 Escaping behavioral lock-in and modeling challenges

Of the various types of lock-in identified, behavioral lock-in seems to be the most difficult to surmount. Policymakers cannot apply standard policy instruments to influence deeply entrenched behavior and may even fear the controversy of attempting to do so. It nevertheless remains a transition bottleneck, especially when the transition desired involves substantial consumer-led technology adoption. Furthermore, building a model of technology transitions that incorporates human behavior and decision making is already controversial since modelers may fundamentally disagree on *why* individuals make the decisions they do, and how that decision making should be modeled in the first place. Take, for example, the case of the energy efficiency gap, which describes the slow uptake of energy efficient technologies that occurs, despite their purported superiority in the long run. There is a gap between the realized diffusion rate and that which would result should *rational* positive net present value investments be the decision paradigm. Behavioral economists suggest that a policy approach of *libertarian paternalism* could lead to better decision making while not ex-ante eliminating alternatives or distorting economic incentives (Gillingham and Palmer, 2014). Indeed, behavioral economists believe that these suboptimal choices are not due to lack of information but instead due to confounding preferences, decision heuristics, and social interactions (Seto et al., 2016). This approach consists of "nudges", a re-framing or re-contextualization of decision alternatives, that may lead to "better" decisions. Implementing nudges to escape behavioral lock-in essentially involves a schema of non-financial policy instruments, which are largely unexplored in the technology transitions literature. It is worthwhile to study how non-financial policy instruments, in addition to, or in lieu of financial policy instruments could stimulate a technology transition. In the section above, we suggested that innovation in niches could spill-over to consumers, influencing their technology adoption decisions without direct economic incentive. How does this happen, and if it does, how could a policymaker take advantage of that positive feedback? We suggest that technology transition models deserve a stronger representation of behavioral lock-in that would indicate how policy efforts could reverse habit-formed and socially ingrained decision biases and failures.

5.2.3 Technology leap-frogging

In terms of long-term, global climate change mitigation efforts, researchers have their eye on developing countries. Developing countries largely operate on primitive primary energy sources, have large populations, and if historical energy transitions are any indication, their transition to cleaner, more sustainable primary energy sources that we currently see in developed economies entails a dangerous commitment of GHG emissions. Technological leap-frogging, or the concept that such developing economies could skip over historical energy transitions and accelerate into sustainable energy systems, is touted as a solution to rapid global decarbonization. Indeed, leap-frogging has the potential to avoid the infrastructural and institutional carbon lock-ins, while contributing to climate change mitigation, and offering substantial improvements in economic productivity and quality of life. Unfortunately, however, inducing technological leap-frogging is not at all straightforward. First, as is the case globally, sustainable energy technologies remain somewhat cost-prohibitive. Even if, for example, the net present value of investment in a natural-gas fired power plant exceeds that of a coal fired power plant, credit may not be available and infrastructure may not be in place to commit to that investment. In relatively poor communities without reliable electricity or heating and cooling, carbon intensity is not the first priority. Furthermore, endogenous changes in energy demands complicates the matter. Using a technology transition model to explore how leap-frogging could occur entails modeling the interactions among the various lock-in types.

Above all, we believe the advances described in this dissertation represent a fundamental stepping-stone to this new paradigm of technology transition modeling. And finally, we are optimistic that such a combination of perspective and technique could lead to substantially better technology policy decision making, especially when it will become crucially important. A number of crucial research questions remain unanswered, and we believe operations research models can contribute substantive solutions.

5.3 Are these models ready for primetime?

Studying technology transitions is not merely an academic exercise. Indeed, the current and anticipated consequences of climate change have prompted researchers from a variety of disciplines to seek to understand how a policymaker may influence or accelerate a technology transition. Unfortunately, technology policy has been fraught with missteps and failures, in part, we hypothesize, because of the sheer complexity of understanding the processes by which technology transitions occur.

This dissertation has been written in order to advance the modeling of technology transitions and the role of policy support. Our models yielded valuable insights and have paved the way for ever more creative and parsimonious modeling approaches. While these models are theoretical, each real-world case study demonstrates how they can be parameterized with data from other sources and produce intuitive results, validating our modeling approaches. Further, they have inspired what we believe could be a real paradigm shift in the modeling. What remains to be answered is: are these models ready for primetime? That is, do these models have the capability of informing real-world technology policy? In short, yes, but no work is ever complete. That is, there will always be an opportunity for more extensions, more complexity, new methodologies, etc.

We reiterate here that the development of each model in Chapters 2, 3, and 4 was followed by an illustrative case study to demonstrate how our modeling approach could inform real-world technology policy. These case studies speak for themselves, but we would never recommend that a policymaker limit her decision making to the results of any one model. As an example, take the specific case studies evaluated in this dissertation and suppose a policymaker wishes to mitigate climate change by using public money to affect technological change. Each of the three modeling approaches provides a different perspective and answers different questions, but ultimately complements each other. To make this point clear, take the diffusion of electric vehicles as an example. Specifically, the energy system optimization model in Chapter 2 will demonstrate how the diffusion of electric vehicles might play out *vis-a-vis* intermittent renewable electricity generation and battery charging and discharging activity. The Markov models of Chapter 3 "zoom-in" on the development or diffusion of electric vehicles to determine how the policymaker should support electric vehicle development in the face of uncertain R&D outcomes. Finally, the bilevel optimization model of Chapter 4 explores the relationship between adoption and infrastructure and optimal policy allocation between different actors. While the actual numerical results of these case studies are subject to significant limitations and uncertainties, the general findings that emerge about the technology policy approaches most likely to be effective – and the contextual factors they most critically depend on – should hold with relatively high confidence. For example, while we cannot confidently recommend that the U.S. federal government should offer a subsidy of exactly \$5167 per BEV charging station, we do believe that the results of the case study in Chapter 4 suggest that the government's policy approach for BEVs should allocate a greater share of public funds to charging infrastructure deployment than it has in recent years.

Indeed, as George Box put it, "all models are wrong, but some are useful." In this way, yes, these models have value, but most importantly, they represent one in a long series of steps towards a better understanding of our impossibly complex world.

Appendices

Appendix A

Proofs of propositions in Chapter 3

A.1 Proof of Proposition 3.1

Linearity:

$$\frac{\partial^2}{\partial r_2^2} WTP^{\mu}_{MRP} = 0 \quad \forall \mu \in \{\mu_1, \mu_2, \mu_{12}\} \tag{A.1}$$

$$\frac{\partial^2}{\partial r_3^2} WTP^{\mu}_{MRP} = 0 \quad \forall \mu \in \{\mu_1, \mu_2, \mu_{12}\} \tag{A.2}$$

$$\frac{\partial^2}{\partial {r_2}^2} WTP^{\pi}_{MDP} = 0 \quad \forall \pi \in \{\pi_1, \pi_2\} \tag{A.3}$$

$$\frac{\partial^2}{\partial {r_3}^2} WTP^{\pi}_{MDP} = 0 \quad \forall \pi \in \{\pi_1, \pi_2\} \tag{A.4}$$

Directions of the effects:

$$\frac{\partial}{\partial r_2} WTP^{\mu_1}_{MRP} = \frac{(p'-p)(1-\delta+\delta q+\delta s)(1-\delta)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{A.5}$$

$$\frac{\partial}{\partial r_3} WTP^{\mu_1}_{MRP} = \frac{(p'-p)(1-\delta+\delta q+\delta s)(\delta q)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{A.6}$$

$$\begin{array}{rcl}\frac{\partial}{\partial r_2}WTP^{\mu_2}_{MRP} & = & p\delta\frac{(1-\delta)(s-s')-(q'-q)(1-\delta+\delta p)}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} \\ & > & 0 \text{ if } (1-\delta)(s-s') > (q'-q)(1-\delta+\delta p) \\ & < & 0 \text{ otherwise}\end{array} \tag{A.7}$$

$$\frac{\partial}{\partial r_3}WTP^{\mu_2}_{MRP} = \frac{\delta p((q'-q)(1-\delta+\delta p)+\delta(q's-qs'))}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{A.8}$$

$$\begin{array}{rcl}\frac{\partial}{\partial r_2}WTP^{\mu_{12}}_{MRP} & = & \frac{p'}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q')} - \frac{p}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\ & > & 0 \text{ if } (1-\delta)^2(p'-p)+\delta(1-\delta)(p'q-pq') \\ & & +\delta(1-\delta)(p's-ps')+\delta^2 p'p(q-q') > 0 \\ & < & 0 \text{ otherwise}\end{array} \tag{A.9}$$

$$\frac{\partial}{\partial r_3}WTP^{\mu_{12}}_{MRP} = \frac{\delta(1-\delta)(p'q'-pq)+\delta^2 qq'(p'-p)+\delta^2(p'q's-pqs')+\delta^2 pp'(q'-q)}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{A.10}$$

$$\frac{\partial}{\partial r_2}WTP^{\pi_1}_{MDP} = \frac{(p'-p)(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{A.11}$$

$$\frac{\partial}{\partial r_3}WTP^{\pi_1}_{MDP} = \frac{(p'-p)\delta q}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{A.12}$$

$$\begin{array}{rcl}\frac{\partial}{\partial r_2}WTP^{\pi_2}_{MDP} & = & \frac{(1-\delta)(s-s')-(q'-q)(1-\delta+\delta p)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\ & < & 0 \text{ if } (q'-q)(1-\delta+\delta p) > (1-\delta)(s-s') \\ & > & 0 \text{ otherwise}\end{array} \tag{A.13}$$

$$\frac{\partial}{\partial r_3}WTP^{\pi_2}_{MDP} = \frac{(q'-q)(1-\delta+\delta p)+\delta(q's-qs')(1-\delta+\delta p)/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{A.14}$$

A.2 Proof of Proposition 3.2

$$\frac{\partial}{\partial p} WTP^{\mu_1}_{MRP} = \frac{-(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{A.15}$$

$$\frac{\partial^2}{\partial p^2} WTP^{\mu_1}_{MRP} = \frac{2\delta(1-\delta+\delta q)(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{A.16}$$

$$\frac{\partial}{\partial q} WTP^{\mu_2}_{MRP} = \frac{-\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{A.17}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\mu_2}_{MRP} = \frac{(2)(\delta(1-\delta)+\delta^2 p)\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{A.18}$$

$$\frac{\partial}{\partial p} WTP^{\mu_{12}}_{MRP} = \frac{-(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{A.19}$$

$$\frac{\partial^2}{\partial p^2} WTP^{\mu_{12}}_{MRP} = \frac{2\delta(1-\delta+\delta q)(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{A.20}$$

$$\frac{\partial}{\partial q} WTP^{\mu_{12}}_{MRP} = \frac{-\delta p(1-\delta+\delta p)(r_3-r_2)-\delta^2 p s r_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{A.21}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\mu_{12}}_{MRP} = 2(\delta(1-\delta)+\delta^2 p)\frac{\delta p(1-\delta+\delta p)(r_3-r_2)+\delta^2 p s r_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{A.22}$$

$$\frac{\partial}{\partial p} WTP^{\pi_1}_{MDP} = \frac{-((r_2(1-\delta)+\delta q r_3))((1-\delta)(1-\delta+\delta q+\delta s))-p'((r_2(1-\delta)+\delta q r_3)\delta(1-\delta+\delta q))}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{A.23}$$

$$\frac{\partial^2}{\partial p^2} WTP^{\pi_1}_{MDP} > 0 \text{ (by inspection of Eq. (B.91))} \tag{A.24}$$

$$\frac{\partial}{\partial q} WTP^{\pi_2}_{MDP} < 0 \text{ (the algebraic quantity is omitted here for space)} \tag{A.25}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\pi_2}_{MDP} > 0 \text{ (the algebraic quantity is omitted here for space)} \tag{A.26}$$

A.3 Proof of Proposition 3.3

$$\frac{\partial}{\partial s} WTP^{\mu_2}_{MRP} = \frac{pr_2\delta(1-\delta)+\delta^2 pqr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} > 0 \tag{A.27}$$

$$\frac{\partial^2}{\partial s^2} WTP^{\mu_2}_{MRP} = \frac{-2pr_2\delta^2(1-\delta)^2-2\delta^3(1-\delta)pqr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} < 0 \tag{A.28}$$

$$\frac{\partial}{\partial s} WTP^{\pi_2}_{MDP} > 0 \text{ (the algebraic quantity is omitted here for space)} \tag{A.29}$$

$$\frac{\partial^2}{\partial s^2} WTP^{\pi_2}_{MDP} < 0 \text{ (the algebraic quantity is omitted here for space)} \tag{A.30}$$

A.4 Proof of Proposition 3.4

$$\frac{\partial}{\partial p'}WTP^{\mu_1}_{MRP} = \frac{(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^2} > 0 \tag{A.31}$$

$$\frac{\partial^2}{\partial p'^2}WTP^{\mu_1}_{MRP} = \frac{(-2)(\delta)(1-\delta+\delta q)(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^3} < 0 \tag{A.32}$$

$$\frac{\partial}{\partial q'}WTP^{\mu_2}_{MRP} = \frac{\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^2} > 0 \tag{A.33}$$

$$\frac{\partial^2}{\partial q'^2}WTP^{\mu_2}_{MRP} = \frac{(-2)(\delta(1-\delta)+\delta^2 p)\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^3} < 0 \tag{A.34}$$

$$\frac{\partial}{\partial p'}WTP^{\pi_1}_{MDP} = \frac{r_2(1-\delta)+\delta q r_3}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{A.35}$$

$$\frac{\partial^2}{\partial p'^2}WTP^{\pi_1}_{MDP} = 0 \tag{A.36}$$

$$\frac{\partial}{\partial q'}WTP^{\pi_2}_{MDP} = \frac{(1-\delta+\delta p)(r_3-r_2+\delta s r_3/(1-\delta))}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{A.37}$$

$$\frac{\partial^2}{\partial q'^2}WTP^{\pi_2}_{MDP} = 0 \tag{A.38}$$

A.5 Proof of Proposition 3.5

$$
\begin{aligned}
\frac{\partial}{\partial s} WTP^{\mu_1}_{MRP} &= \delta(r_2(1-\delta)+\delta q r_3)\Big(\tfrac{p}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} \\
&\quad -\tfrac{p'}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^2}\Big) \\
&> 0 \text{ if } s < (1-\delta+\delta q)\big(\tfrac{\sqrt{p'p}}{1-\delta}-\tfrac{1}{\delta}\big) \\
&= 0 \text{ if } s = (1-\delta+\delta q)\big(\tfrac{\sqrt{p'p}}{1-\delta}-\tfrac{1}{\delta}\big) \\
&< 0 \text{ if } s > (1-\delta+\delta q)\big(\tfrac{\sqrt{p'p}}{1-\delta}-\tfrac{1}{\delta}\big)
\end{aligned} \tag{A.39}
$$

$$
\begin{aligned}
\frac{\partial^2}{\partial s^2} WTP^{\mu_1}_{MRP} &= 2\delta^2(1-\delta)(r_2(1-\delta)+\delta q r_3)\Big(\tfrac{p'}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^3} \\
&\quad -\tfrac{p}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3}\Big) \\
&< 0 \text{ if } s < (1-\delta+\delta q)\big(\tfrac{\sqrt[3]{p'p}(\sqrt[3]{p'}+\sqrt[3]{p})}{1-\delta}-\tfrac{1}{\delta}\big) \\
&= 0 \text{ if } s = (1-\delta+\delta q)\big(\tfrac{\sqrt[3]{p'p}(\sqrt[3]{p'}+\sqrt[3]{p})}{1-\delta}-\tfrac{1}{\delta}\big) \\
&> 0 \text{ if } s > (1-\delta+\delta q)\big(\tfrac{\sqrt[3]{p'p}(\sqrt[3]{p'}+\sqrt[3]{p})}{1-\delta}-\tfrac{1}{\delta}\big)
\end{aligned} \tag{A.40}
$$

$$
\frac{\partial}{\partial s} WTP^{\pi_1}_{MDP} = \frac{-\delta(1-\delta)(p'-p)(r_2(1-\delta)+\delta q r_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{A.41}
$$

$$
\frac{\partial^2}{\partial s^2} WTP^{\pi_1}_{MDP} = \frac{2\delta^2(1-\delta)^2(p'-p)(r_2(1-\delta)+\delta q r_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{A.42}
$$

A.6 Proof of Proposition 3.6

See Eq. (A.39) above.

$$
\begin{aligned}
\frac{\partial}{\partial q} WTP^{\mu_1}_{MRP} \quad &= \quad \frac{\delta p' r_3(1-\delta+\delta s+\delta p')-p' r_2 \delta(1-\delta+p')}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q)} - \frac{\delta p r_3(1-\delta+\delta s+\delta p)-p r_2 \delta(1-\delta+p)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\
&> \quad 0 \text{ if } q < \frac{A(1-\delta+\delta s+\delta p')(1-\delta)-(1-\delta+\delta s+\delta p)(1-\delta)}{\delta(1-\delta)+\delta^2 p-A(\delta(1-\delta)+\delta^2 p')} \\
&= \quad 0 \text{ if } q = \frac{A(1-\delta+\delta s+\delta p')(1-\delta)-(1-\delta+\delta s+\delta p)(1-\delta)}{\delta(1-\delta)+\delta^2 p-A(\delta(1-\delta)+\delta^2 p')} \\
&< \quad 0 \text{ if } q > \frac{A(1-\delta+\delta s+\delta p')(1-\delta)-(1-\delta+\delta s+\delta p)(1-\delta)}{\delta(1-\delta)+\delta^2 p-A(\delta(1-\delta)+\delta^2 p')} \\
\text{where} \quad & A = \sqrt{\frac{\delta p r_3(1-\delta+\delta s+\delta p)-p r_2 \delta(1-\delta+p)}{\delta p' r_3(1-\delta+\delta s+\delta p')-p' r_2 \delta(1-\delta+p')}}
\end{aligned}
\tag{A.43}
$$

$$
\begin{aligned}
\frac{\partial}{\partial p} WTP^{\mu_2}_{MRP} \quad &= \quad \frac{(1-\delta+\delta q'+\delta s')(r_2(1-\delta)+\delta q' r_3)}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^2} - \frac{(1-\delta+\delta q+\delta s)(r_2(1-\delta)+\delta q r_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} \\
&> \quad 0 \text{ if } p < \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
& \quad\quad \text{and } \delta(1-\delta+\delta q) - A\delta(1-\delta+\delta q') < 0 \\
&> \quad 0 \text{ if } p > \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
& \quad\quad \text{and } \delta(1-\delta+\delta q) - A\delta(1-\delta+\delta q') > 0 \\
\text{where} \quad & A = \sqrt{\frac{(1-\delta+\delta q+\delta s)(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q'+\delta s')(r_2(1-\delta)+\delta q' r_3)}}
\end{aligned}
\tag{A.44}
$$

$$
\begin{aligned}
\frac{\partial}{\partial p} WTP^{\pi_2}_{MDP} \quad &> \quad 0 \text{ if } (q'-q)(r_3-r_2)\delta^2(1-\delta)s + \delta^3 r_3(q's-qs')s \\
& \quad\quad -r_2(1-\delta)(s-s')\delta(1-\delta+\delta q) > 0 \\
&< \quad 0 \text{ otherwise}
\end{aligned}
\tag{A.45}
$$

$$
\begin{aligned}
\frac{\partial^2}{\partial p^2} WTP^{\pi_2}_{MDP} \quad &< \quad 0 \text{ if } \frac{\partial}{\partial p} WTP^{\pi_2}_{MDP} > 0 \\
&> 0 \quad \text{otherwise}
\end{aligned}
\tag{A.46}
$$

Appendix B

Material supplemental to Chapter 3

B.1 Derivation of WTPs in the MRP model

The system of equations that defines the value functions of the MRP under parameterization μ_0 is given in Eq. (B.1). Rewards are received upon transitions to States 2 and 3. Once this system of equations is solved, we do not need to repeat the process for the other parameterizations; by symmetry, we solve all four systems by solving one.

$$\begin{cases} v^{\mu_0}_{MRP}(1) = pr_2 + \delta(1-p)v^{\mu_0}_{MRP}(1) + \delta p v^{\mu_0}_{MRP}(2) \\ v^{\mu_0}_{MRP}(2) = (1-q-s)r_2 + qr_3 + \delta s v^{\mu_0}_{MRP}(1) + \delta(1-q-s)v^{\mu_0}_{MRP}(2) + \delta q v^{\mu_0}_{MRP}(3) \\ v^{\mu_0}_{MRP}(3) = r_3 + \delta v^{\mu_0}_{MRP}(3) \end{cases} \tag{B.1}$$

Via substitution, beginning with $v^{\mu_0}_{MRP}(3)$, the solution for $v^{\mu_0}_{MRP}(1)$ is given in Eq. (B.2).

$$v^{\mu_0}_{MRP}(1) = \frac{pr_2 + \delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta) + \delta p(1-\delta+\delta q)} \tag{B.2}$$

By exploiting symmetry, we can construct all WTP expressions for parameterizations μ_1, μ_2, and μ_{12}. These are given in Eqs. (B.3–B.5) below.

$$
\begin{aligned}
WTP^{\mu_1}_{MRP} &= v^{\mu_1}_{MRP}(1) - v^{\mu_0}_{MRP}(1) \\
&= \tfrac{p'r_2+\delta p'qr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q)} - \tfrac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\
&= \tfrac{(p'-p)(1-\delta+\delta q+\delta s)(r_2(1-\delta)+\delta qr_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))}
\end{aligned} \tag{B.3}
$$

$$
\begin{aligned}
WTP^{\mu_2}_{MRP} &= v^{\mu_2}_{MRP}(1) - v^{\mu_0}_{MRP}(1) \\
&= \tfrac{pr_2+\delta pq'r_3/(1-\delta)}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q')} - \tfrac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\
&= \tfrac{(r_3-r_2)(q'-q)\delta p(1-\delta+\delta p)+pr_2\delta(1-\delta)(s-s')+\delta^2 pr_3(q's-qs')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))}
\end{aligned} \tag{B.4}
$$

$$
\begin{aligned}
WTP^{\mu_{12}}_{MRP} &= v^{\mu_{12}}_{MRP}(1) - v^{\mu_0}_{MRP}(1) \\
&= \tfrac{p'r_2+\delta p'q'r_3/(1-\delta)}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q')} - \tfrac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\
&= \tfrac{(r_3-r_2)(q'-q)\delta^2 p'p+(p'r_2(1-\delta)+\delta p'q'r_3)(1-\delta+\delta q+\delta s)-(pr_2(1-\delta)+\delta pqr_3)(1-\delta+\delta q'+\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))}
\end{aligned} \tag{B.5}
$$

We note that all WTPs are non-negative, given the natural conditions $p' \geq p$, $q' \geq q$, $r_3 \geq r_2$, $s \leq s'$, and $\delta \in (0,1)$. The corollaries are proven by setting $s = s' = 0$, and then simplifying.

B.2 Comparative statics analysis of WTPs in the MRP model

B.2.1 Comparative statics of $WTP^{\mu_1}_{MRP}$ in the general case

$$
\tfrac{\partial}{\partial p} WTP^{\mu_1}_{MRP} = \tfrac{-(r_2(1-\delta)+\delta qr_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{B.6}
$$

$$
\tfrac{\partial}{\partial p'} WTP^{\mu_1}_{MRP} = \tfrac{(r_2(1-\delta)+\delta qr_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^2} > 0 \tag{B.7}
$$

$$
\begin{aligned}
\frac{\partial}{\partial q}WTP^{\mu_1}_{MRP} &= \tfrac{\delta p' r_3(1-\delta+\delta s+\delta p')-p' r_2\delta(1-\delta+p')}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q)} - \tfrac{\delta p r_3(1-\delta+\delta s+\delta p)-p r_2\delta(1-\delta+p)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\
&> 0 \text{ if } q < \tfrac{A(1-\delta+\delta s+\delta p')(1-\delta)-(1-\delta+\delta s+\delta p)(1-\delta)}{\delta(1-\delta)+\delta^2 p-A(\delta(1-\delta)+\delta^2 p')} \\
&= 0 \text{ if } q = \tfrac{A(1-\delta+\delta s+\delta p')(1-\delta)-(1-\delta+\delta s+\delta p)(1-\delta)}{\delta(1-\delta)+\delta^2 p-A(\delta(1-\delta)+\delta^2 p')} \\
&< 0 \text{ if } q > \tfrac{A(1-\delta+\delta s+\delta p')(1-\delta)-(1-\delta+\delta s+\delta p)(1-\delta)}{\delta(1-\delta)+\delta^2 p-A(\delta(1-\delta)+\delta^2 p')} \\
\text{where } & A = \sqrt{\tfrac{\delta p r_3(1-\delta+\delta s+\delta p)-p r_2\delta(1-\delta+p)}{\delta p' r_3(1-\delta+\delta s+\delta p')-p' r_2\delta(1-\delta+p')}}
\end{aligned} \tag{B.8}
$$

$$
\begin{aligned}
\frac{\partial}{\partial s}WTP^{\mu_1}_{MRP} &= \delta(r_2(1-\delta)+\delta q r_3)\Big(\tfrac{p}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} \\
&\quad -\tfrac{p'}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^2}\Big) \\
&> 0 \text{ if } s < (1-\delta+\delta q)\Big(\tfrac{\sqrt{p' p}}{1-\delta} - \tfrac{1}{\delta}\Big) \\
&= 0 \text{ if } s = (1-\delta+\delta q)\Big(\tfrac{\sqrt{p' p}}{1-\delta} - \tfrac{1}{\delta}\Big) \\
&< 0 \text{ if } s > (1-\delta+\delta q)\Big(\tfrac{\sqrt{p' p}}{1-\delta} - \tfrac{1}{\delta}\Big)
\end{aligned} \tag{B.9}
$$

$$
\frac{\partial}{\partial r_2}WTP^{\mu_1}_{MRP} = \tfrac{(p'-p)(1-\delta+\delta q+\delta s)(1-\delta)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{B.10}
$$

$$
\frac{\partial}{\partial r_3}WTP^{\mu_1}_{MRP} = \tfrac{(p'-p)(1-\delta+\delta q+\delta s)(\delta q)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{B.11}
$$

$$
\frac{\partial^2}{\partial p^2}WTP^{\mu_1}_{MRP} = \tfrac{2\delta(1-\delta+\delta q)(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{B.12}
$$

$$
\frac{\partial^2}{\partial p'^2}WTP^{\mu_1}_{MRP} = \tfrac{(-2)(\delta)(1-\delta+\delta q)(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^3} < 0 \tag{B.13}
$$

$$
\text{Computing the sign of } \frac{\partial^2}{\partial q^2}WTP^{\mu_1}_{MRP} \text{ is algebraically intractable.} \tag{B.14}
$$

$$
\begin{aligned}
\frac{\partial^2}{\partial s^2} WTP^{\mu_1}_{MRP} &= 2\delta^2(1-\delta)(r_2(1-\delta)+\delta q r_3)(\tfrac{p'}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q))^3} \\
&\quad -\tfrac{p}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3}) \\
&< 0 \text{ if } s < (1-\delta+\delta q)(\tfrac{\sqrt[3]{p'p}(\sqrt[3]{p'}+\sqrt[3]{p})}{1-\delta} - \tfrac{1}{\delta}) \\
&= 0 \text{ if } s = (1-\delta+\delta q)(\tfrac{\sqrt[3]{p'p}(\sqrt[3]{p'}+\sqrt[3]{p})}{1-\delta} - \tfrac{1}{\delta}) \\
&> 0 \text{ if } s > (1-\delta+\delta q)(\tfrac{\sqrt[3]{p'p}(\sqrt[3]{p'}+\sqrt[3]{p})}{1-\delta} - \tfrac{1}{\delta})
\end{aligned} \tag{B.15}
$$

$$
\frac{\partial^2}{\partial r_2^2} WTP^{\mu_1}_{MRP} = 0 \tag{B.16}
$$

$$
\frac{\partial^2}{\partial r_3^2} WTP^{\mu_1}_{MRP} = 0 \tag{B.17}
$$

B.2.2 Comparative statics of $WTP^{\mu_1}_{MRP}$ in the special case

$$
\frac{\partial}{\partial p} WTP^{\mu_1}_{MRP} = \frac{-r_2(1-\delta)-\delta q r_3}{(1-\delta+\delta q)(1-\delta+\delta p)^2} < 0 \tag{B.18}
$$

$$
\frac{\partial}{\partial p'} WTP^{\mu_1}_{MRP} = \frac{r_2(1-\delta)+\delta q r_3}{(1-\delta+\delta q)(1-\delta+\delta p')^2} > 0 \tag{B.19}
$$

$$
\frac{\partial}{\partial q} WTP^{\mu_1}_{MRP} = \frac{(p'-p)(r_3-r_2)\delta(1-\delta)}{(1-\delta+\delta q)^2(1-\delta+\delta p)(1-\delta+\delta p')} > 0 \tag{B.20}
$$

$$
\frac{\partial}{\partial r_2} WTP^{\mu_1}_{MRP} = \frac{(p'-p)(1-\delta)}{(1-\delta+\delta q)(1-\delta+\delta p)(1-\delta+\delta p')} > 0 \tag{B.21}
$$

$$
\frac{\partial}{\partial r_3} WTP^{\mu_1}_{MRP} = \frac{\delta q(p'-p)}{(1-\delta+\delta q)(1-\delta+\delta p)(1-\delta+\delta p')} > 0 \tag{B.22}
$$

$$\frac{\partial^2}{\partial p^2} WTP^{\mu_1}_{MRP} = 2\delta \frac{r_2(1-\delta)+\delta q r_3}{(1-\delta+\delta q)(1-\delta+\delta p')^3} > 0 \tag{B.23}$$

$$\frac{\partial^2}{\partial p'^2} WTP^{\mu_1}_{MRP} = (-2\delta) \frac{r_2(1-\delta)+\delta q r_3}{(1-\delta+\delta q)(1-\delta+\delta p')^3} < 0 \tag{B.24}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\mu_1}_{MRP} < 0 \text{ (by inspection of Eq. (B.20))} \tag{B.25}$$

$$\frac{\partial^2}{\partial r_2^2} WTP^{\mu_1}_{MRP} = 0 \tag{B.26}$$

$$\frac{\partial^2}{\partial r_3^2} WTP^{\mu_1}_{MRP} = 0 \tag{B.27}$$

B.2.3 Comparative statics of $WTP^{\mu_2}_{MRP}$ in the general case

$$\begin{aligned}
\frac{\partial}{\partial p} WTP^{\mu_2}_{MRP} &= \frac{(1-\delta+\delta q'+\delta s')(r_2(1-\delta)+\delta q' r_3)}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^2} - \frac{(1-\delta+\delta q+\delta s)(r_2(1-\delta)+\delta q r_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} \\
&> 0 \text{ if } p < \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
&\quad \text{and } \delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q') < 0 \\
&> 0 \text{ if } p > \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
&\quad \text{and } \delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q') > 0 \\
\text{where} &\quad A = \sqrt{\frac{(1-\delta+\delta q+\delta s)(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q'+\delta s')(r_2(1-\delta)+\delta q' r_3)}} \\
&= 0 \text{ if } p = \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
&< 0 \text{ if } p > \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
&\quad \text{and } \delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q') < 0 \\
&< 0 \text{ if } p < \frac{A(1-\delta+\delta q'+\delta s')(1-\delta)-(1-\delta+\delta q+\delta s)(1-\delta)}{\delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q')} \\
&\quad \text{and } \delta(1-\delta+\delta q)-A\delta(1-\delta+\delta q') > 0
\end{aligned} \tag{B.28}$$

$$\frac{\partial}{\partial q} WTP^{\mu_2}_{MRP} = \frac{-\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{B.29}$$

$$\frac{\partial}{\partial s} WTP^{\mu_2}_{MRP} = \frac{pr_2\delta(1-\delta)+\delta^2 pqr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} > 0 \tag{B.30}$$

$$\frac{\partial}{\partial q'} WTP^{\mu_2}_{MRP} = \frac{\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^2} > 0 \tag{B.31}$$

$$\frac{\partial}{\partial s'} WTP^{\mu_2}_{MRP} = \frac{-pr_2\delta(1-\delta)-\delta^2 pq'r_3}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^2} < 0 \tag{B.32}$$

$$\begin{aligned} \frac{\partial}{\partial r_2} WTP^{\mu_2}_{MRP} &= p\delta \frac{(1-\delta)(s-s')-(q'-q)(1-\delta+\delta p)}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} \\ &> 0 \text{ if } (1-\delta)(s-s') > (q'-q)(1-\delta+\delta p) \\ &< 0 \text{ otherwise} \end{aligned} \tag{B.33}$$

$$\frac{\partial}{\partial r_3} WTP^{\mu_2}_{MRP} = \frac{\delta p((q'-q)(1-\delta+\delta p)+\delta(q's-qs'))}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{B.34}$$

$$\text{Computing the sign of } \frac{\partial^2}{\partial p^2} WTP^{\mu_2}_{MRP} \text{ is algebraically intractable.} \tag{B.35}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\mu_2}_{MRP} = \frac{(2)(\delta(1-\delta)+\delta^2 p)\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{B.36}$$

$$\frac{\partial^2}{\partial s^2} WTP^{\mu_2}_{MRP} = \frac{-2pr_2\delta^2(1-\delta)^2-2\delta^3(1-\delta)pqr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} < 0 \tag{B.37}$$

$$\frac{\partial^2}{\partial q'^2}WTP^{\mu_2}_{MRP} = \frac{(-2)(\delta(1-\delta)+\delta^2 p)\delta p((r_3-r_2)(1-\delta+\delta p)+r_3\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^3} < 0 \tag{B.38}$$

$$\frac{\partial^2}{\partial s'^2}WTP^{\mu_2}_{MRP} = \frac{2pr_2\delta^2(1-\delta)^2+2\delta^3(1-\delta)pq'r_3}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q'))^3} > 0 \tag{B.39}$$

$$\frac{\partial^2}{\partial r_2'^2}WTP^{\mu_2}_{MRP} = 0 \tag{B.40}$$

$$\frac{\partial^2}{\partial r_3'^2}WTP^{\mu_2}_{MRP} = 0 \tag{B.41}$$

B.2.4 Comparative statics of $WTP^{\mu_2}_{MRP}$ in the special case

$$\frac{\partial}{\partial p}WTP^{\mu_2}_{MRP} = \frac{\delta(1-\delta)(r_3-r_2)(q'-q)}{(1-\delta+\delta q')(1-\delta+\delta q)(1-\delta+\delta p)^2} > 0 \tag{B.42}$$

$$\frac{\partial}{\partial q}WTP^{\mu_2}_{MRP} = \frac{-\delta p(r_3-r_2)}{(1-\delta+\delta p)(1-\delta+\delta q)^2} < 0 \tag{B.43}$$

$$\frac{\partial}{\partial q'}WTP^{\mu_2}_{MRP} = \frac{\delta p(r_3-r_2)}{(1-\delta+\delta p)(1-\delta+\delta q')^2} > 0 \tag{B.44}$$

$$\frac{\partial}{\partial r_2}WTP^{\mu_2}_{MRP} = \frac{-(q'-q)\delta p}{(1-\delta+\delta q')(1-\delta+\delta q)(1-\delta+\delta p)} < 0 \tag{B.45}$$

$$\frac{\partial}{\partial r_3}WTP^{\mu_2}_{MRP} = \frac{(q'-q)\delta p}{(1-\delta+\delta q')(1-\delta+\delta q)(1-\delta+\delta p)} > 0 \tag{B.46}$$

$$\frac{\partial^2}{\partial p^2}WTP^{\mu_2}_{MRP} = \frac{-2\delta^2(1-\delta)(r_3-r_2)(q'-q)}{(1-\delta+\delta q')(1-\delta+\delta q)(1-\delta+\delta p)^3} < 0 \tag{B.47}$$

$$\frac{\partial^2}{\partial q^2} WTP_{MRP}^{\mu_2} = \frac{2\delta^2 p(r_3 - r_2)}{(1-\delta+\delta p)(1-\delta+\delta q')^3} > 0 \tag{B.48}$$

$$\frac{\partial^2}{\partial q'^2} WTP_{MRP}^{\mu_2} = \frac{-2\delta^2 p(r_3 - r_2)}{(1-\delta+\delta p)(1-\delta+\delta q')^3} < 0 \tag{B.49}$$

$$\frac{\partial^2}{\partial r_2^2} WTP_{MRP}^{\mu_2} = 0 \tag{B.50}$$

$$\frac{\partial^2}{\partial r_3^2} WTP_{MRP}^{\mu_2} = 0 \tag{B.51}$$

B.2.5 Comparative statics of $WTP_{MRP}^{\mu_{12}}$ in the general case

$$\frac{\partial}{\partial p} WTP_{MRP}^{\mu_{12}} = \frac{-(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{B.52}$$

$$\frac{\partial}{\partial p'} WTP_{MRP}^{\mu_{12}} = \frac{(r_2(1-\delta)+\delta q' r_3)(1-\delta+\delta q'+\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))^2} > 0 \tag{B.53}$$

$$\frac{\partial}{\partial q} WTP_{MRP}^{\mu_{12}} = \frac{-\delta p(1-\delta+\delta p)(r_3-r_2)-\delta^2 psr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{B.54}$$

$$\frac{\partial}{\partial q'} WTP_{MRP}^{\mu_{12}} = \frac{\delta p'(1-\delta+\delta p')(r_3-r_2)+\delta^2 p's'r_3}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))^2} > 0 \tag{B.55}$$

$$\frac{\partial}{\partial s} WTP_{MRP}^{\mu_{12}} = \frac{pr_2\delta(1-\delta)+\delta^2 pqr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} > 0 \tag{B.56}$$

$$\frac{\partial}{\partial s'} WTP_{MRP}^{\mu_{12}} = \frac{-p'r_2\delta(1-\delta)-\delta^2 p'q'r_3}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))^2} < 0 \tag{B.57}$$

$$\begin{aligned}\frac{\partial}{\partial r_2}WTP^{\mu_{12}}_{MRP} &= \tfrac{p'}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q')} - \tfrac{p}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\ &> 0 \text{ if } (1-\delta)^2(p'-p)+\delta(1-\delta)(p'q-pq') \\ &\quad +\delta(1-\delta)(p's-ps')+\delta^2 p'p(q-q')>0 \\ &< 0 \text{ otherwise}\end{aligned} \tag{B.58}$$

$$\frac{\partial}{\partial r_3}WTP^{\mu_{12}}_{MRP} = \tfrac{\delta(1-\delta)(p'q'-pq)+\delta^2 qq'(p'-p)+\delta^2(p'q's-pqs')+\delta^2 pp'(q'-q)}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))} > 0 \tag{B.59}$$

$$\frac{\partial^2}{\partial p^2}WTP^{\mu_{12}}_{MRP} = \tfrac{2\delta(1-\delta+\delta q)(r_2(1-\delta)+\delta q r_3)(1-\delta+\delta q+\delta s)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{B.60}$$

$$\frac{\partial^2}{\partial p'^2}WTP^{\mu_{12}}_{MRP} = \tfrac{-2\delta(1-\delta+\delta q')(r_2(1-\delta)+\delta q' r_3)(1-\delta+\delta q'+\delta s')}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))^3} < 0 \tag{B.61}$$

$$\frac{\partial^2}{\partial q^2}WTP^{\mu_{12}}_{MRP} = 2(\delta(1-\delta)+\delta^2 p)\tfrac{\delta p(1-\delta+\delta p)(r_3-r_2)+\delta^2 psr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{B.62}$$

$$\frac{\partial^2}{\partial q'^2}WTP^{\mu_{12}}_{MRP} = -2(\delta(1-\delta)+\delta^2 p')\tfrac{\delta p'(1-\delta+\delta p')(r_3-r_2)+\delta^2 p's'r_3}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))^3} < 0 \tag{B.63}$$

$$\frac{\partial^2}{\partial s^2}WTP^{\mu_{12}}_{MRP} = -2\delta(1-\delta)\tfrac{pr_2\delta(1-\delta)+\delta^2 pqr_3}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} < 0 \tag{B.64}$$

$$\frac{\partial^2}{\partial s'^2}WTP^{\mu_{12}}_{MRP} = 2\delta(1-\delta)\tfrac{p'r_2\delta(1-\delta)+\delta^2 p'q'r_3}{((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q'))^3} > 0 \tag{B.65}$$

$$\frac{\partial^2}{\partial r_2^2} WTP_{MRP}^{\mu_{12}} = 0 \tag{B.66}$$

$$\frac{\partial^2}{\partial r_3^2} WTP_{MRP}^{\mu_{12}} = 0 \tag{B.67}$$

B.2.6 Comparative statics of $WTP_{MRP}^{\mu_{12}}$ in the special case

$$\frac{\partial}{\partial p} WTP_{MRP}^{\mu_{12}} = \frac{-r_2(1-\delta)-\delta q r_3}{(1-\delta+\delta q)(1-\delta+\delta p)^2} < 0 \tag{B.68}$$

$$\frac{\partial}{\partial p'} WTP_{MRP}^{\mu_{12}} = \frac{r_2(1-\delta)+\delta q' r_3}{(1-\delta+\delta q')(1-\delta+\delta p')^2} > 0 \tag{B.69}$$

$$\frac{\partial}{\partial q} WTP_{MRP}^{\mu_{12}} = \frac{-\delta p(r_3-r_2)}{(1-\delta+\delta p)(1-\delta+\delta q)^2} < 0 \tag{B.70}$$

$$\frac{\partial}{\partial q'} WTP_{MRP}^{\mu_{12}} = \frac{\delta p'(r_3-r_2)}{(1-\delta+\delta p')(1-\delta+\delta q')^2} > 0 \tag{B.71}$$

$$\begin{array}{rcl} \frac{\partial}{\partial r_2} WTP_{MRP}^{\mu_{12}} & = & \frac{p'}{(1-\delta+\delta q')(1-\delta+\delta p')} - \frac{p}{(1-\delta+\delta q)(1-\delta+\delta p)} \\ & > & 0 \text{ if } (1-\delta)^2(p'-p) + \delta(1-\delta)(p'q-pq') \\ & & +\delta^2 p'p(q-q') > 0 \\ & < & 0 \text{ otherwise} \end{array} \tag{B.72}$$

$$\frac{\partial}{\partial r_3} WTP_{MRP}^{\mu_{12}} = \frac{\delta(1-\delta)(p'q'-pq)+\delta^2 qq'(p'-p)+\delta^2 pp'(q'-q)}{(1-\delta+\delta q')(1-\delta+\delta p')(1-\delta+\delta q)(1-\delta+\delta p)} > 0 \tag{B.73}$$

$$\frac{\partial^2}{\partial p^2} WTP_{MRP}^{\mu_{12}} = \frac{2\delta(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q)(1-\delta+\delta p)^3} > 0 \tag{B.74}$$

$$\frac{\partial^2}{\partial p'^2} WTP^{\mu_{12}}_{MRP} = \frac{-2\delta(r_2(1-\delta)+\delta q' r_3)}{(1-\delta+\delta q')(1-\delta+\delta p')^3} < 0 \tag{B.75}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\mu_{12}}_{MRP} = \frac{2\delta^2 p(r_3-r_2)}{(1-\delta+\delta p)(1-\delta+\delta q)^3} > 0 \tag{B.76}$$

$$\frac{\partial^2}{\partial q'^2} WTP^{\mu_{12}}_{MRP} = \frac{-2\delta^2 p'(r_3-r_2)}{(1-\delta+\delta p')(1-\delta+\delta q')^3} < 0 \tag{B.77}$$

$$\frac{\partial^2}{\partial r_2^2} WTP^{\mu_{12}}_{MRP} = 0 \tag{B.78}$$

$$\frac{\partial^2}{\partial r_3^2} WTP^{\mu_{12}}_{MRP} = 0 \tag{B.79}$$

B.3 Derivation of WTPs in the MDP model

The system of equations that defines the value functions of the MDP under policy π_0 is given in Eq. (B.80). Rewards are received upon transitions to States 2 and 3.

$$\begin{cases} v^{\pi_0}_{MDP}(1) = pr_2 + \delta(1-p)v^{\pi_0}_{MDP}(1) + \delta p v^{\pi_0}_{MDP}(2) \\ v^{\pi_0}_{MDP}(2) = (1-q-s)r_2 + qr_3 + \delta s v^{\pi_0}_{MDP}(1) + \delta(1-q-s)v^{\pi_0}_{MDP}(2) + \delta q v^{\pi_0}_{MDP}(3) \\ v^{\pi_0}_{MDP}(3) = r_3 + \delta v^{\pi_0}_{MDP}(3) \end{cases} \tag{B.80}$$

We note that, since no cost is incurred under policy π_0, the system of equations above is essentially the same as the system of equations for policy μ_0 in the MRP model (see Eq. (B.2)). We therefore have

$$v^{\pi_0}_{MDP}(1) = \frac{pr_2 + \delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta) + \delta p(1-\delta+\delta q)}. \tag{B.81}$$

The system of equations that defines the value functions of the MDP under policy π_1 is given in Eq. (B.80).

$$\begin{cases} v^{\pi_1}_{MDP}(1) = -c^{\pi_1}_{MDP} + p'r_2 + \delta(1-p')v^{\pi_1}_{MDP}(1) + \delta p' v^{\pi_1}_{MDP}(2) \\ v^{\pi_1}_{MDP}(2) = (1-q-s)r_2 + qr_3 + \delta s v^{\pi_0}_{MDP}(1) + \delta(1-q-s)v^{\pi_0}_{MDP}(2) + \delta q v^{\pi_0}_{MDP}(3) \\ v^{\pi_1}_{MDP}(3) = r_3 + \delta v^{\pi_0}_{MDP}(3) \end{cases} \tag{B.82}$$

We solve the system in Eq. (B.82) by substitution, beginning with $v^{\pi_1}_{MDP}(3)$. The solution is given in Eq. (B.83).

$$v^{\pi_1}_{MDP}(1) = \frac{p'r_2 + \delta p' q r_3/(1-\delta) - c^{\pi_1}_{MDP}(1-\delta+\delta q+\delta s)}{(1-\delta+\delta q+\delta s)(1-\delta) + \delta p'(1-\delta+\delta q)} \tag{B.83}$$

We derive $WTP^{\pi_1}_{MDP}$ in Eq. (B.84) below.

$$\begin{aligned} WTP^{\pi_1}_{MDP} &= \{c^{\pi_1}_{MDP} : v^{\pi_1}_{MDP}(1) = v^{\pi_0}_{MDP}(1)\} \\ &= \{c^{\pi_1}_{MDP} : \tfrac{p'r_2+\delta p' q r_3/(1-\delta) - c^{\pi_1}_{MDP}(1-\delta+\delta q+\delta s)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p'(1-\delta+\delta q)} = \tfrac{pr_2+\delta p q r_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)}\} \\ &= \tfrac{(p'-p)(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \end{aligned} \tag{B.84}$$

The system of equations that defines the value functions of the MDP under policy π_2 is given in Eq. (B.85).

$$\begin{cases} v^{\pi_2}_{MDP}(1) = pr_2 + \delta(1-p)v^{\pi_2}_{MDP}(1) + \delta p v^{\pi_2}_{MDP}(2) \\ v^{\pi_2}_{MDP}(2) = -c^{\pi_2}_{MDP} + (1-q'-s')r_2 + q'r_3 + \delta s' v^{\pi_2}_{MDP}(1) + \delta(1-q'-s')v^{\pi_2}_{MDP}(2) + \delta q' v^{\pi_2}_{MDP}(3) \\ v^{\pi_2}_{MDP}(3) = r_3 + \delta v^{\pi_2}_{MDP}(3) \end{cases} \tag{B.85}$$

We solve the system in Eq. (B.85) by substitution, beginning with $v^{\pi_2}_{MDP}(3)$. The solution is given in Eq. (B.86).

$$v_{MDP}^{\pi_2}(1) = \frac{pr_2 + \delta pq'r_3/(1-\delta) - \delta pc_{MDP}^{\pi_2}}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q')} \tag{B.86}$$

We derive $WTP_{MDP}^{\pi_2}$ in Eq. (B.87) below.

$$\begin{aligned} WTP_{MDP}^{\pi_2} &= \{c_{MDP}^{\pi_2} : v_{MDP}^{\pi_2}(1) = v_{MDP}^{\pi_0}(1)\} \\ &= \{c_{MDP}^{\pi_2} : \tfrac{pr_2+\delta pq'r_3/(1-\delta)-\delta pc_{MDP}^{\pi_2}}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p(1-\delta+\delta q')} = \tfrac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)}\} \\ &= \tfrac{(q'-q)(r_3-r_2)(1-\delta+\delta p)+r_2(1-\delta)(s-s')+\delta r_3(q's-qs')(1-\delta+\delta p)/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \end{aligned} \tag{B.87}$$

If $s = s' = 0$, $WTP_{MDP}^{\pi_2} = \frac{(q'-q)(r_3-r_2)}{1-\delta+\delta q}$.

The system of equations that defines the value functions of the MDP under policy π_{12} is given in Eq. (B.88).

$$\begin{cases} v_{MDP}^{\pi_{12}}(1) = -c_{MDP}^{\pi_{12}} + p'r_2 + \delta(1-p')v_{MDP}^{\pi_{12}}(1) + \delta p'v_{MDP}^{\pi_{12}}(2) \\ v_{MDP}^{\pi_{12}}(2) = -c_{MDP}^{\pi_{12}} + (1-q'-s')r_2 + q'r_3 + \delta s'v_{MDP}^{\pi_{12}}(1) + \delta(1-q'-s')v_{MDP}^{\pi_{12}}(2) + \delta q'v_{MDP}^{\pi_{12}}(3 \\ v_{MDP}^{\pi_{12}}(3) = r_3 + \delta v_{MDP}^{\pi_{12}}(3) \end{cases} \tag{B.88}$$

We solve the system in Eq. (B.88) by substitution, beginning with $v_{MDP}^{\pi_{12}}(3)$. The solution is given in Eq. (B.89).

$$v_{MDP}^{\pi_{12}}(1) = \frac{p'r_2 + \delta p'q'r_3/(1-\delta) - c_{MDP}^{\pi_{12}}(1-\delta+\delta q'+\delta s'+\delta p')}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q')} \tag{B.89}$$

We derive $WTP_{MDP}^{\pi_{12}}$ in Eq. (B.90) below.

$$\begin{aligned} WTP_{MDP}^{\pi_{12}} &= \{c_{MDP}^{\pi_{12}} : v_{MDP}^{\pi_{12}}(1) = v_{MDP}^{\pi_0}(1)\} \\ &= \{c_{MDP}^{\pi_{12}} : \tfrac{p'r_2+\delta p'q'r_3/(1-\delta)-c_{MDP}^{\pi_{12}}(1-\delta+\delta q'+\delta s'+\delta p')}{(1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+\delta q')} = \tfrac{pr_2+\delta pqr_3/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)}\} \\ &= \tfrac{(p'r_2+\delta p'q'r_3/(1-\delta))((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))-(pr_2+\delta pqr_3/(1-\delta))((1-\delta+\delta q'+\delta s')(1-\delta)+\delta p'(1-\delta+}{1-\delta+\delta q'+\delta s'+\delta p'} \end{aligned} \tag{B.90}$$

B.3.1 Comparative statics of $WTP^{\pi_1}_{MDP}$ in the general case

$$\frac{\partial}{\partial p}WTP^{\pi_1}_{MDP} = \frac{-((r_2(1-\delta)+\delta q r_3))((1-\delta)(1-\delta+\delta q+\delta s))-p'((r_2(1-\delta)+\delta q r_3)\delta(1-\delta+\delta q))}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{B.91}$$

$$\frac{\partial}{\partial p'}WTP^{\pi_1}_{MDP} = \frac{r_2(1-\delta)+\delta q r_3}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{B.92}$$

$$\begin{aligned}\frac{\partial}{\partial q}WTP^{\pi_1}_{MDP} &= (p'-p)\delta(1-\delta)\frac{r_3(1-\delta+\delta p+\delta s)-r_2(1-\delta+\delta p)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} \\ &> 0 \text{ if } r_3 > r_2\end{aligned} \tag{B.93}$$

$$\frac{\partial}{\partial s}WTP^{\pi_1}_{MDP} = \frac{-\delta(1-\delta)(p'-p)(r_2(1-\delta)+\delta q r_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^2} < 0 \tag{B.94}$$

$$\frac{\partial}{\partial r_2}WTP^{\pi_1}_{MDP} = \frac{(p'-p)(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{B.95}$$

$$\frac{\partial}{\partial r_3}WTP^{\pi_1}_{MDP} = \frac{(p'-p)\delta q}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{B.96}$$

$$\frac{\partial^2}{\partial p^2}WTP^{\pi_1}_{MDP} > 0 \text{ (by inspection of Eq. (B.91))} \tag{B.97}$$

$$\frac{\partial^2}{\partial p'^2}WTP^{\pi_1}_{MDP} = 0 \tag{B.98}$$

$$\frac{\partial^2}{\partial q^2}WTP^{\pi_1}_{MDP} = \frac{-2\delta^2(1-\delta)(1-\delta+\delta p)(p'-p)(r_3(1-\delta+\delta p+\delta s)-r_2(1-\delta+\delta p))}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} < 0 \tag{B.99}$$

$$\frac{\partial^2}{\partial s^2} WTP^{\pi_1}_{MDP} = \frac{2\delta^2(1-\delta)^2(p'-p)(r_2(1-\delta)+\delta q r_3)}{((1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q))^3} > 0 \tag{B.100}$$

$$\frac{\partial^2}{\partial {r_2}^2} WTP^{\pi_1}_{MDP} = 0 \tag{B.101}$$

$$\frac{\partial^2}{\partial {r_3}^2} WTP^{\pi_1}_{MDP} = 0 \tag{B.102}$$

B.3.2 Comparative statics of $WTP^{\pi_1}_{MDP}$ in the special case

$$\frac{\partial}{\partial p} WTP^{\pi_1}_{MDP} = \frac{-(1-\delta+\delta p')(r_2(1-\delta)+\delta q r_3)}{(1-\delta+\delta q)(1-\delta+\delta p)^2} < 0 \tag{B.103}$$

$$\frac{\partial}{\partial p'} WTP^{\pi_1}_{MDP} = \frac{r_2(1-\delta)+\delta q r_3}{(1-\delta+\delta q)(1-\delta+\delta p)} \tag{B.104}$$

$$\frac{\partial}{\partial q} WTP^{\pi_1}_{MDP} = \frac{(r_3-r_2)(p'-p)\delta(1-\delta)}{(1-\delta+\delta p)(1-\delta+\delta q)^2} > 0 \tag{B.105}$$

$$\frac{\partial}{\partial r_2} WTP^{\pi_1}_{MDP} = \frac{(p'-p)(1-\delta)}{(1-\delta+\delta q)(1-\delta+\delta p)} > 0 \tag{B.106}$$

$$\frac{\partial}{\partial r_3} WTP^{\pi_1}_{MDP} = \frac{(p'-p)\delta q}{(1-\delta+\delta q)(1-\delta+\delta p)} > 0 \tag{B.107}$$

$$\frac{\partial^2}{\partial p^2} WTP^{\pi_1}_{MDP} > 0 \text{ (by inspection of Eq. (B.103))} \tag{B.108}$$

$$\frac{\partial^2}{\partial p'^2} WTP^{\pi_1}_{MDP} = 0 \tag{B.109}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\pi_1}_{MDP} = \frac{-2(r_3-r_2)(p'-p)\delta^2(1-\delta)}{(1-\delta+\delta p)(1-\delta+\delta q)^3} < 0 \tag{B.110}$$

$$\frac{\partial^2}{\partial {r_2}^2} WTP^{\pi_1}_{MDP} = 0 \tag{B.111}$$

$$\frac{\partial^2}{\partial {r_3}^2} WTP^{\pi_1}_{MDP} = 0 \tag{B.112}$$

B.3.3 Comparative statics of $WTP^{\pi_2}_{MDP}$ in the general case

$$\begin{array}{rcl} \frac{\partial}{\partial p} WTP^{\pi_2}_{MDP} & > & 0 \text{ if } (q'-q)(r_3-r_2)\delta^2(1-\delta)s + \delta^3 r_3(q's-qs')s \\ & & -r_2(1-\delta)(s-s')\delta(1-\delta+\delta q) > 0 \\ & < & 0 \text{ otherwise} \end{array} \tag{B.113}$$

$$\frac{\partial}{\partial q} WTP^{\pi_2}_{MDP} < 0 \text{ (the algebraic quantity is omitted here for space)} \tag{B.114}$$

$$\frac{\partial}{\partial q'} WTP^{\pi_2}_{MDP} = \frac{(1-\delta+\delta p)(r_3-r_2+\delta s r_3/(1-\delta))}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{B.115}$$

$$\frac{\partial}{\partial s} WTP^{\pi_2}_{MDP} > 0 \text{ (the algebraic quantity is omitted here for space)} \tag{B.116}$$

$$\frac{\partial}{\partial s'} WTP^{\pi_2}_{MDP} = \frac{-r_2(1-\delta)-\delta r_3 q(1-\delta+\delta p)/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} < 0 \tag{B.117}$$

$$\begin{aligned}\frac{\partial}{\partial r_2} WTP^{\pi_2}_{MDP} &= \tfrac{(1-\delta)(s-s')-(q'-q)(1-\delta+\delta p)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} \\ &< 0 \text{ if } (q'-q)(1-\delta+\delta p) > (1-\delta)(s-s') \\ &> 0 \text{ otherwise}\end{aligned} \tag{B.118}$$

$$\frac{\partial}{\partial r_3} WTP^{\pi_2}_{MDP} = \tfrac{(q'-q)(1-\delta+\delta p)+\delta(q's-qs')(1-\delta+\delta p)/(1-\delta)}{(1-\delta+\delta q+\delta s)(1-\delta)+\delta p(1-\delta+\delta q)} > 0 \tag{B.119}$$

$$\begin{aligned}\frac{\partial^2}{\partial p^2} WTP^{\pi_2}_{MDP} \quad &< \quad 0 \text{ if } \tfrac{\partial}{\partial p} WTP^{\pi_2}_{MDP} > 0 \\ &> 0 \quad \text{otherwise}\end{aligned} \tag{B.120}$$

$$\frac{\partial^2}{\partial q^2} WTP^{\pi_2}_{MDP} > 0 \text{ (the algebraic quantity is omitted here for space)} \tag{B.121}$$

$$\frac{\partial^2}{\partial q'^2} WTP^{\pi_2}_{MDP} = 0 \tag{B.122}$$

$$\frac{\partial^2}{\partial s^2} WTP^{\pi_2}_{MDP} < 0 \text{ (the algebraic quantity is omitted here for space)} \tag{B.123}$$

$$\frac{\partial^2}{\partial s'^2} WTP^{\pi_2}_{MDP} = 0 \tag{B.124}$$

$$\frac{\partial^2}{\partial r_2^2} WTP^{\pi_2}_{MDP} = 0 \tag{B.125}$$

$$\frac{\partial^2}{\partial r_3^2} WTP^{\pi_2}_{MDP} = 0 \tag{B.126}$$

B.3.4 Comparative statics of $WTP_{MDP}^{\pi_2}$ in the special case

$$\frac{\partial}{\partial p}WTP_{MDP}^{\pi_2} = 0 \tag{B.127}$$

$$\frac{\partial}{\partial q}WTP_{MDP}^{\pi_2} = \frac{-(r_3-r_2)(1-\delta+\delta q')}{(1-\delta+\delta q)^2} < 0 \tag{B.128}$$

$$\frac{\partial}{\partial q'}WTP_{MDP}^{\pi_2} = \frac{r_3-r_2}{1-\delta+\delta q} > 0 \tag{B.129}$$

$$\frac{\partial}{\partial r_2}WTP_{MDP}^{\pi_2} = \frac{-(q'-q)}{1-\delta+\delta q} < 0 \tag{B.130}$$

$$\frac{\partial}{\partial r_3}WTP_{MDP}^{\pi_2} = \frac{q'-q}{1-\delta+\delta q} > 0 \tag{B.131}$$

$$\frac{\partial}{\partial \delta}WTP_{MDP}^{\pi_2} = \frac{(q'-q)(r_3-r_2)(1-q)}{(1-\delta+\delta q)^2} > 0 \tag{B.132}$$

$$\frac{\partial^2}{\partial p^2}WTP_{MDP}^{\pi_2} = 0 \tag{B.133}$$

$$\frac{\partial^2}{\partial q^2}WTP_{MDP}^{\pi_2} = \frac{2\delta(r_3-r_2)(1-\delta+\delta q')}{(1-\delta+\delta q)^3} > 0 \tag{B.134}$$

$$\frac{\partial^2}{\partial q'^2}WTP_{MDP}^{\pi_2} = 0 \tag{B.135}$$

$$\frac{\partial^2}{\partial r_2^2}WTP_{MDP}^{\pi_2} = 0 \tag{B.136}$$

$$\frac{\partial^2}{\partial r_3^2} WTP^{\pi_2}_{MDP} = 0 \tag{B.137}$$

Appendix C

Proofs of propositions in and material supplemental to Chapter 4

C.1 Coefficients of the objective function in Eq. (4.9)

The coefficients of the objective function of the quadratic program in Eq. (4.9) are as below,

$$h_1 = -\beta_c - \frac{\beta_b \beta_c}{2(b-\beta_b)} \tag{C.1a}$$

$$h_2 = \frac{-a}{2(b-\beta_b)} \tag{C.1b}$$

$$h_3 = \frac{-\beta_b a - \beta_c}{2(b-\beta_b)} \tag{C.1c}$$

$$h_4 = \alpha\beta_c + \frac{\alpha\beta_b\beta_c}{2(b-\beta_b)} - \frac{\beta_b(K-ac)}{2(b-\beta_b)} - K \tag{C.1d}$$

$$h_5 = \frac{\alpha\beta_b a - (K-ac)}{2(b-\beta_b)} \tag{C.1e}$$

$$h_6 = \alpha K + \frac{\alpha\beta_b(K-ac)}{2(b-\beta_b)} \tag{C.1f}$$

C.2 Proofs of propositions

C.2.1 Proof of Proposition 4.1

The infrastructure firm's optimal response $y^*(\pi_A, \pi_I)$ solves,

$$\max_{y(\pi_A,\pi_I)\geq 0} p(y)y - (c-\pi_I)y = \max_{y(\pi_A,\pi_I)\geq 0} \left[\frac{\beta_c \pi_A + K}{a} - \frac{b-\beta_b}{a} y\right] y - (c-\pi_I)y.$$

Therefore, the first order condition for a maximum is,

$$\frac{\beta_c \pi_A + K}{a} - \frac{2(b - \beta_b)}{a} y - (c - \pi_I) = 0,$$

and the second order condition $-\frac{b-\beta_b}{a} < 0$ holds, since $b > \beta_b$, by assumption. It remains to check whether this local maximum satisfies the non-negativity constraint, as in,

$$y^*(\pi_A, \pi_I) = \begin{cases} \frac{-a(c-\pi_I)+\beta_c\pi_A+K}{2(b-\beta_b)}, & \text{if } \frac{\beta_c\pi_A+K}{a} \geq c - \pi_I \\ 0, & \text{o.w.} \end{cases}$$

$\square$.

C.2.2 Proof of Proposition 4.2

Follows from Remarks 4.1, 4.2, and 4.3. The Hessian matrix $\boldsymbol{H}$ is obtained by partial differentiation of the upper level objective function of Eq. (4.5), when $\frac{-a(c-\pi_I)+\beta_c\pi_A+K}{2(b-\beta_b)}$ is substituted for y. $\square$.

C.2.3 Proof of Proposition 4.3

A twice continuously differentiable function is convex on a convex set if and only if the Hessian matrix of second order partial derivatives is negative semi-definite (Fletcher, 2013, Chapter 10). Next, the Hessian matrix is negative semi-definite if and only if its eigenvalues are all non-positive (Anthony and Harvey, 2012, Chapter 11). For clarity of exposition, we write the Hessian matrix in shorthand,

$$\boldsymbol{H} = \begin{pmatrix} -2\beta_c - \frac{2\beta_b\beta_c}{2(b-\beta_b)} & \frac{-\beta_b a - \beta_c}{2(b-\beta_b)} \\ \frac{-\beta_b a - \beta_c}{2(b-\beta_b)} & \frac{-2a}{2(b-\beta_b)} \end{pmatrix} = \begin{pmatrix} H_1 & H_2 \\ H_2 & H_3 \end{pmatrix},$$

noting $H_1 < 0$, $H_2 < 0$, and $H_3 < 0$. The eigenvalues $\boldsymbol{\lambda}$ solve $\det(\boldsymbol{H} - \boldsymbol{\lambda} I) = 0$, where I is the 2x2 identity matrix, giving

$$\boldsymbol{\lambda} = \begin{pmatrix} \lambda_1 \\ \lambda_2 \end{pmatrix} = \begin{pmatrix} \frac{H_1+H_3+\sqrt{(H_1-H_3)^2+4H_2^2}}{2} \\ \frac{H_1+H_3-\sqrt{(H_1-H_3)^2+4H_2^2}}{2} \end{pmatrix}.$$

By inspection, $\lambda_2 \leq 0$ and $\lambda_1 \leq 0 \iff H_1 + H_3 + \sqrt{(H_1 - H_3)^2 + 4H_2^2} \leq 0 \iff 8\beta_c ab - 6\beta_b\beta_c a \geq \beta_b^2 a^2 + \beta_c^2$. The feasible region is convex since it is defined as the intersection of linear constraints, and so the quadratic program is convex if and only if $8\beta_c ab - 6\beta_b\beta_c a \geq \beta_b^2 a^2 + \beta_c^2$. $\square$.

C.2.4 Proof of Proposition 4.4

C.2.4.1 Program A1

Program A1 is (strictly) convex if and only if the coefficient $h_1 < 0$, which holds by inspection of Eq. (C.1a) above. The feasible region is the intersection of linear constraints, so it is convex. $\square$.

C.2.4.2 Program A2

Program A2 is (strictly) convex if and only if the coefficient $h_2 + \frac{a^2 h_1}{\beta_c^2} - \frac{a h_3}{\beta_c} < 0 \iff b > \beta_b$, which is true by assumption. The feasible region is the intersection of linear constraints, so it is convex. $\square$.

C.2.4.3 Program B1

Program B1 is (strictly) convex if and only if the coefficient $h_2 - \frac{h_3^2}{4h_1} < 0 \iff 8\beta_c ab - 6\beta_b\beta_c a > \beta_b^2 a^2 + \beta_c^2$. The feasible region is the intersection of linear constraints, so it is convex. $\square$.

The solution to maximizing a single variable concave-up quadratic function with bound constraints lies at one of the bounds. To show this, we wish to solve $\max_{x \in X} f(\cdot)$, where $X = \{x : l \leq x \leq u\} \neq \varnothing$ and $f(\cdot)$ is concave-up. Suppose $x \in X$ and without loss of generality suppose $f(l) \geq f(u)$. We can write x as a convex combination of the lower and upper bounds as $x = \lambda l + (1 - \lambda)u$, where $0 \leq \lambda \leq 1$. Then, $f(x) = f(\lambda l + (1 - \lambda)u) \leq \lambda f(l) + (1 - \lambda) f(u) \leq \lambda f(l) + (1 - \lambda) f(l) = f(l)$, where the first inequality holds by convexity of $f(\cdot)$ (concave-up) and the second by assumption that $f(l) \geq f(u)$. That is, for arbitrary $x \in X$, we always have $f(x) \leq f(l)$, and l maximizes $f(\cdot)$ over X. Generally, therefore, the solution to $\max_{x \in X} f(\cdot)$ is $\max(f(l), f(u))$. $\square$.

C.2.4.4 Program B2

Program B2 is (strictly) convex if and only if the coefficient $h_2 + \frac{a^2 h_1}{\beta_c^2} - \frac{a h_3}{\beta_c} < 0 \iff b > \beta_b$, which is true by assumption. The feasible region is the intersection of linear constraints, so it is convex. $\square$.

Bibliography

Aghion, P., Howitt, P., 1992. A Model of Growth Through Creative Destruction. Econometrica 60, 323.

Alizamir, S., De Véricourt, F., Sun, P., 2016. Efficient feed-in-tariff policies for renewable energy technologies. Operations Research 64, 52–66.

Anadon, L.D., Nemet, G.F., 2014. The U.S. Synthetic Fuels Corporation: Policy Consistency, Flexibility, and the Long-Term Consequences of Perceived Failures, in: Grubler, A., Wilson, C. (Eds.), Energy Technology Innovation: Learning from Historical Successes and Failures. Cambridge University Press, New York, NY. chapter 19, pp. 257–272.

Anandarajah, G., McDowall, W., Ekins, P., 2013. Decarbonising road transport with hydrogen and electricity: Long term global technology learning scenarios. International Journal of Hydrogen Energy 38, 3419–3432.

Anthony, M., Harvey, M., 2012. Linear Algebra: Concepts and Methods. 1st ed., Cambridge University Press, Cambridge, U.K.

Arthur, W.B., 1989. Competing Technologies, Increasing Returns, and Lock-In by Historical Events. The Economic Journal 99, 116–131.

Arthur, W.B., 2014. Complexity Economics: A Different Framework for Economic Thought, in: Complexity and the Economy. Oxford University Press, pp. 1–22.

Arthur, W.B., Ermoliev, Y.M., Kaniovski, Y.M., 1987. Path-dependent processes and the emergence of macro-structure. European Journal of Operational Research 30, 294–303.

Arthur, W.B., Lane, D.A., 1993. Information Contagion. Structural Change and Economic Dynamics 4, 81–104.

Austin Chamber of Commerce, 2018. Population. URL: https://www.austinchamber.com/economic-development/austin-profile/population.

Austin Energy, 2010. Austin Energy Resource, Generation, and Climate Protection Plan to 2020. Technical Report. Austin Energy.

Austin Energy, 2017. Power Plants, Austin Energy.

Austin Energy, 2018. Austin Energy. URL: https://austinenergy.com/ae/.

Baker, E., Bosetti, V., Salo, A., 2020. Robust portfolio decision analysis: An application to the energy research and development portfolio problem. European Journal of Operational Research 284, 1107–1120.

Baker, E., Chon, H., Keisler, J., 2010. Battery technology for electric and hybrid vehicles: Expert views about prospects for advancement. Technological Forecasting and Social Change 77, 1139–1146.

Bass, F.M., 1969. A New Product Growth for Model Consumer Durables. Management Science 15, 215–227.

Bass, F.M., Krishnan, T.V., Jain, D.C., 1994. Why the Bass Model Fits without Decision Variables. Marketing Science 13, 203–223.

Bertsekas, D.P., 2012. Dynamic programming and optimal control. 4th ed. ed., Athena Scientific, Belmont, Mass.

Bian, J., Zhao, X., 2020. Tax or subsidy? An analysis of environmental policies in supply chains with retail competition. European Journal of Operational Research 283, 901–914.

Blanford, G.J., 2009. R&D investment strategy for climate change. Energy Economics 31, S27–S36.

Bosetti, V., Carraro, C., Massetti, E., Sgobbi, A., Tavoni, M., 2009. Optimal energy investment and R&D strategies to stabilize atmospheric greenhouse gas concentrations. Resource and Energy Economics 31, 123–137.

Bosetti, V., Longden, T., 2013. Light duty vehicle transportation and global climate policy: The importance of electric drive vehicles. Energy Policy 58, 209–219.

Bosetti, V., Tavoni, M., 2009. Uncertain R&D, backstop technology and GHGs stabilization. Energy Economics 31, S18–S26.

van Bree, B., Verbong, G.P., Kramer, G.J., 2010. A multi-level perspective on the introduction of hydrogen and battery-electric vehicles. Technological Forecasting and Social Change 77, 529–540.

Brozynski, M., Leibowicz, B., 2018. Decarbonizing power and transportation at the urban scale: An analysis of the Austin, Texas Community Climate Plan. Sustainable Cities and Society 43.

Brozynski, M.T., Leibowicz, B.D., in press. Markov models of policy support for technology transitions. European Journal of Operational Research .

Butter, F., den Hofkes, M., 2006. A neo-classical economics viewpoint on technological transitions, in: Olsthoorn, X., Wieczoreck, A. (Eds.), Understanding Industrial Transformation: Views from Different Disciplines. Springer, Dordrecht, the Netherlands, pp. 141–162.

C40 Cities, 2018a. C40 Cities. URL: http://www.c40.org/.

C40 Cities, 2018b. Consumption-based GHG emissions of C40 cities.

CapMetro, 2016. Fast Facts, Capital Metropolitan Transit Authority, Austin, TX.

Center for Climate and Energy Solutions, 2018. Global Emissions. URL: https://www.c2es.org/content/international-emissions/.

Cervigni, R., Liden, R., Neumann, J., Strzepek, K., 2015. Enhancing the Climate Resilience of Africa's Infrastructure. The World Bank, Washington, D.C.

Chemama, J., Cohen, M.C., Lobel, R., Perakis, G., 2019. Consumer subsidies with a strategic supplier: Commitment vs. flexibility. Management Science 65, 681–713.

Cheng, C., 2019. The 5G wireless revolution, explained. URL: https://www.cnet.com/news/the-5g-wireless-revolution-explained/.

Cho, S.H., McCardle, K.F., 2009. The adoption of multiple dependent technologies. Operations Research 57, 157–169.

Choi, D.G., Kreikebaum, F., Thomas, V.M., Divan, D., 2013. Coordinated EV adoption: Double-digit reductions in emissions and fuel use for $40/vehicle-year. Environmental Science and Technology 47, 10703–10707.

City of Austin, 2007. Resolution No. 20070215-023. Technical Report. Austin City Council. Austin, TX.

City of Austin, 2014. Resolution No. 20140828-157. Technical Report. Austin City Council. Austin, TX.

City of Austin, 2015. Austin Community Climate Plan. City of Austin Office of Sustainability, Austin, TX.

City of Austin, 2016. Implementation Plan: Phase I. Technical Report. City of Austin Office of Sustainability. Austin, TX.

Cohen, M.C., Lobel, R., Perakis, G., 2016. The impact of demand uncertainty on consumer subsidies for green technology adoption. Management Science 62, 1235–1258.

Cohen, W.M., 2015. Innovation and technological change, economics of, in: International Encyclopedia of the Social Behavioral Sciences. 2nd ed.. Elsevier, pp. 160–168.

Coleman, J., Katz, E., Menzel, H., 1957. The Diffusion of an Innovation Among Physicians. Sociometry 20, 253–270.

Comodi, G., Cioccolanti, L., Gargiulo, M., 2012. Municipal scale scenario: Analysis of an Italian seaside town with MarkAL-TIMES. Energy Policy 41, 303–315.

David, P.A., 1985. Clio and the Economics of QWERTY. The American Economic Review 75, 332–337.

DOE, 2020. New all-electric vehicles. URL: https://www.fueleconomy.gov/feg/findacar.shtml.

DOT, 2015. The National Transit Database, 2015, Federal Transit Administration, United States Department of Transportation.

DOT, 2017. National Household Travel Survey, 2009, Federal Highway Administration, United States Department of Transportation.

Edelenbosch, O.Y., McCollum, D.L., van Vuuren, D.P., Bertram, C., Carrara, S., Daly, H., Fujimori, S., Kitous, A., Kyle, P., Ó Broin, E., Karkatsoulis, P., Sano, F., 2017. Decomposing passenger transport futures: Comparing results of global integrated assessment models. Transportation Research Part D: Transport and Environment 55, 281–293.

EIA, 2017. Annual Energy Outlook, 2017, EIA.

EIA, 2020. How much carbon dioxide is produced per kilowatthour of u.s. electricity generation? URL: https://www.eia.gov/tools/faqs/faq.php?id=74&t=11.

Encarnação, S., Santos, F.P., Santos, F.C., Blass, V., Pacheco, J.M., Portugali, J., 2018. Paths to the adoption of electric vehicles: An evolutionary game theoretical approach. Transportation Research Part B: Methodological 113, 24–33.

EPA, 2017a. Greenhouse Gas Emissions from a Typical Passenger Vehicle, 2017, EPA.

EPA, 2017b. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2017 .

EPA, 2018. Greenhouse gas emissions from a typical passenger vehicle. URL: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle.

ERCOT, 2015. Hourly Load Data (South Central Region), 2015-2017, ERCOT.

ERCOT, 2017a. Hourly Wind Generation 2015, ERCOT.

ERCOT, 2017b. Monthly Forecast of Peak Demand and Energy, 2017, ERCOT.

EVAdoption, 2019. EV Market Share by State. URL: https://evadoption.com/ev-market-share/ev-market-share-state/.

Farzin, Y., Huisman, K., Kort, P., 1998. Optimal timing of technology adoption. Journal of Economic Dynamics and Control 22, 779 – 799.

Few, S., Schmidt, O., Offer, G.J., Brandon, N., Nelson, J., Gambhir, A., 2018. Prospective improvements in cost and cycle life of off-grid lithium-ion battery packs: An analysis informed by expert elicitations. Energy Policy 114, 578–590.

FHWA, 2017. Forecasts of Vehicle Miles Traveled (VMT): Spring 2017, Office of Highway Policy Information, Federal Highway Administration.

Fletcher, R., 2013. Practical Methods of Optimization. 2nd ed., Wiley, Hoboken, N.J.

Fouquet, R., 2016a. Historical energy transitions: Speed, prices and system transformation. Energy Research and Social Science 22, 7–12.

Fouquet, R., 2016b. Path dependence in energy systems and economic development. Nature Energy 1.

Geels, F.W., 2002. Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. Research Policy 31, 1257–1274.

Geels, F.W., 2004. From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory. Research Policy 33, 897–920.

Geels, F.W., 2005. Processes and patterns in transitions and system innovations: Refining the co-evolutionary multi-level perspective. Technological Forecasting and Social Change 72, 681–696.

Geels, F.W., 2019. Socio-technical transitions to sustainability: a review of criticisms and elaborations of the Multi-Level Perspective. Current Opinion in Environmental Sustainability 39, 187–201.

Gil, N., Miozzo, M., Massini, S., 2012. The innovation potential of new infrastructure development: An empirical study of Heathrow airport's T5 project. Research Policy 41, 452–466.

Gillingham, K., Palmer, K., 2014. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. Review of Environmental Economics and Policy 8, 18–38.

Glaeser, E.L., Kahn, M.E., 2010. The greenness of cities: Carbon dioxide emissions and urban development. Journal of Urban Economics 67, 404–418.

Gnann, T., Plötz, P., 2015. A review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. Renewable and Sustainable Energy Reviews 47, 783–793.

Greater London Authority, 2016. London's Response to Climate Change, in: The London Plan. London. chapter 5, pp. 176–222.

Griliches, Z., 1957. Hybrid Corn: An Exploration in the Economics of Technological Change. Econometrica 25, 501–522.

Groissböck, M., Pickl, M.J., 2016. An analysis of the power market in Saudi Arabia: Retrospective cost and environmental optimization. Applied Energy 165, 548–558.

Grossman, G.M., Helpman, E., 1991. Quality Ladders in the Theory of Growth. The Review of Economic Studies 58, 43.

Grubler, A., 2012. Energy transitions research: Insights and cautionary tales. Energy Policy 50, 8–16.

Grubler, A., Bai, X., Buettner, T., Dhakal, S., Fisk, D., Ichinose, T., Keirstead, J., Sammer, G., Satterthwaite, D., Schulz, N., Shah, N., Steinberger, J., Weisz, H., 2012. Urban Energy Systems, in: Global Energy Assessment - Toward a Sustainable Future. Cambridge University Press. chapter 18.

Grubler, A., Wilson, C., 2013. Energy Technology Innovation: Learning from Historical Successes and Failures. Cambridge University Press, Cambridge, UK.

Higgins, C.D., Mohamed, M., Ferguson, M.R., 2017. Size matters: How vehicle body type affects consumer preferences for electric vehicles. Transportation Research Part A: Policy and Practice 100, 182–201.

Hillman, T., Ramaswami, A., 2010. Greenhouse Gas Emission Footprints and Energy Use Benchmarks for Eight U.S. Cities. Environmental Science & Technology 44, 1902–1910.

Home Advisor, 2018. True Cost Guide: Install an Electric Vehicle Charging Station. URL: https://www.homeadvisor.com/cost/garages/install-an-electric-vehicle-charging-station/.

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M., Roehrl, A., 2011. OSeMOSYS: The Open Source Energy Modeling System. An introduction to its ethos, structure and development. Energy Policy 39, 5850–5870.

Huétink, F.J., van der Vooren, A., Alkemade, F., 2010. Initial infrastructure development strategies for the transition to sustainable mobility. Technological Forecasting and Social Change 77, 1270–1281.

Hughes, T., 1987. The evolution of large technological systems, in: Bijker, W., Hughes, T., Pinch, T. (Eds.), The Social Construction of Technological Systems. Cambridge, MA, pp. 51–82.

Hughes, T.P., 2012. The evolution of large technological systems. The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology: Anniversary Edition , 45–76.

Huisman, K.J.M., 2001. Technology investment: A game theoretic real options approach. Kluwer Academic Publishers.

ICLEI, 2012. U.S. Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions. Technical Report. ICLEI – Local Governments for Sustainability USA.

IEA, 2019. TCEP: Electric vehicles. URL: https://www.iea.org/tcep/transport/electricvehicles/.

IEA, 2020. Total primary energy supply by source. URL: https://www.iea.org/data-and-statistics?country=WORLD&fuel=Energysupply&indicator=Totalprimaryenergysupply(TPES)bysource.

IPCC, 2014. Summary for policymakers, in: Edenhofer, O., R. Pichs-Madruga, Y., Sokona, E., Farahani, S., Kadner, K., Seyboth, A., Adler, I., Baum, S., Brunner, P., Eickemeier, B., Kriemann, J., Savolainen, S., Schlomer, C., von Stechow, T.Z., Minx, J. (Eds.), Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Iyer, G., Hultman, N., Eom, J., McJeon, H., Patel, P., Clarke, L., 2015. Diffusion of low-carbon technologies and the feasibility of long-term climate targets. Technological Forecasting and Social Change 90, 103–118.

Jayadev, G., Leibowicz, B.D., Kutanoglu, E., 2020. U.s. electricity infrastructure of the future: Generation and transmission pathways through 2050. Applied Energy 260.

Ji, Z., Huang, X., 2018. Plug-in electric vehicle charging infrastructure deployment of China towards 2020: Policies, methodologies, and challenges. Renewable and Sustainable Energy Reviews 90, 710–727.

Jiang, Z., Jain, D., 2012. A Generalized Norton-Bass Model for Multigeneration Diffusion. Management Science 58, 1887–1897.

Jones, E.C., Leibowicz, B.D., 2019. Contributions of shared autonomous vehicles to climate change mitigation. Transportation Research Part D 72, 279–298.

Kemp, R., 1994. Technology and the transition to environmental sustainability. The problem of technological regime shifts. Futures 26, 1023–1046.

Kemp, R., Rip, A., Schot, J., Garud, R., Karnoe, P., 2001. Constructing transition paths through the management of niches.

Kemp, R., Schot, J., Hoogma, R., 1998. Regime shifts to sustainability through processes of niche formation: The approach of strategic niche management. Technology Analysis Strategic Management 10, 175–198.

Klaassen, G., Miketa, A., Larsen, K., Sundqvist, T., 2005. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. Ecological Economics 54, 227–240.

Kornish, L.J., 2006. Technology choice and timing with positive network effects. European Journal of Operational Research 173, 268–282.

Leahy, D., Neary, J.P., 1997. Public Policy Towards R&D in Oligopolistic Industries. The American Economic Review 87, 642–662.

Leibowicz, B., 2018a. Policy recommendations for a transition to sustainable mobility based on historical diffusion dynamics of transport systems. Energy Policy 119.

Leibowicz, B.D., 2018b. The cost of policy uncertainty in electric sector capacity planning: Implications for instrument choice. The Electricity Journal 31, 33–41.

Leibowicz, B.D., 2018c. Welfare improvement windows for innovation policy. Research Policy 47, 390–398.

Leibowicz, B.D., Lanham, C.M., Brozynski, M.T., Vázquez-Canteli, J.R., Castejón, N.C., Nagy, Z., 2018. Optimal decarbonization pathways for urban residential building energy services. Applied Energy 230, 1311–1325.

Lenox, C., Dodder, R., Gage, C., Kaplan, O., Loughlin, D., Yelverton, W., 2013. EPA U.S. Nine-region MARKAL Database Documentation , 151.

Lin, J., Cao, B., Cui, S., Wang, W., Bai, X., 2010. Evaluating the effectiveness of urban energy conservation and GHG mitigation measures: The case of Xiamen city, China. Energy Policy 38, 5123–5132.

Löffler, K., Hainsch, K., Burandt, T., Oei, P.Y., Kemfert, C., von Hirschhausen, C., 2017. Designing a Model for the Global Energy System GENeSYS-MOD: An Application of the Open-Source Energy Modeling System (OSeMOSYS). Energies 10, 1468.

Loulou, R., 2007. ETSAP-TIAM: the TIMES integrated assessment model. part II: mathematical formulation. Computational Management Science 5, 41–66.

Loulou, R., Goldstein, G., Noble, K., 2004. Documentation for the MARKAL Family of Models .

Loulou, R., Labriet, M., 2007. ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure. Computational Management Science 5, 7–40.

Ma, G., Lim, M.K., Mak, H.Y., Wan, Z., 2019. Promoting clean technology adoption: To subsidize products or service infrastructure? Service Science 11, 75–95.

Ma, X., Chai, M., Luo, L., Luo, Y., He, W., Li, G., 2015. An assessment on Shanghai's energy and environment impacts of using MARKAL model. Journal of Renewable and Sustainable Energy 7.

MarkLines, 2019. U.S. Sales Volume. URL: https://www.marklines.com/en/statistics/flash_sales/salesfig_usa_2018.

McCardle, K.F., 1985. Information acquisition and the adoption of new technology. Management Science 31, 1372–1389.

Mersky, A.C., Sprei, F., Samaras, C., Qian, Z.S., 2016. Effectiveness of incentives on electric vehicle adoption in Norway. Transportation Research Part D: Transport and Environment 46, 56–68.

Messner, S., Schrattenholzer, L., 2000. MESSAGE-MACRO: Linking an energy supply model with a macroeconomic module and solving it iteratively. Energy 25, 267–282.

Messner, S., Strubegger, M., 1995. User's Guide for MESSAGE III. IIASA Working Paper , WP–95–69.

Morris, C., Jungjohann, A., 2016. Energiewende: The Solution to More Problems Than Climate Change. Springer International Publishing, Cham. pp. 1–14.

Neaimeh, M., Salisbury, S.D., Hill, G.A., Blythe, P.T., Scoffield, D.R., Francfort, J.E., 2017. Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. Energy Policy 108, 474–486.

Nemet, G.F., Kammen, D.M., 2007. U.S. Energy Research and Development: declining investment, increasing need, and the feasibility of expansion. Energy Policy 35, 746–755.

Nemet, G.F., Zipperer, V., Kraus, M., 2018. The valley of death, the technology pork barrell, and public support for large demonstration projects. Energy Policy , 154–167.

Niu, S.C., 2006. A Piecewise-Diffusion Model of New-Product Demands. Operations Research 54, 678–695.

Noble, K., 2012. OSeMOSYS: The Open Source Energy Modeling System, A translation into the General Algebraic Modeling System (GAMS). Royal Institute of Technology Working Paper Series .

Nordhaus, W.D., Boyer, J.G., 1999. Requiem for Kyoto : An Economic Analysis of the Kyoto Protocol. The Energy Journal 20, 93–130.

Norton, J.A., Bass, F.M., 1987. A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products. Management Science 33, 1069–1086.

NREL, 2016. System Advisor Model, NREL.

NREL, 2017. Annual Technology Baseline, 2017, NREL.

Nunes, P., Farias, T., Brito, M.C., 2015. Enabling solar electricity with electric vehicles smart charging. Energy 87, 10–20.

Ostrom, E., 2010. Polycentric systems for coping with collective action and global environmental change. Global Environmental Change 20, 550–557.

Pfenninger, S., Hawkes, A., Keirstead, J., 2014. Energy systems modeling for twenty-first century energy challenges. Renewable and Sustainable Energy Reviews 33, 74–86.

Pietzcker, R.C., Longden, T., Chen, W., Fu, S., Kriegler, E., Kyle, P., Luderer, G., 2014. Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models. Energy 64, 95–108.

Priessner, A., Sposato, R., Hampl, N., 2018. Predictors of electric vehicle adoption: An analysis of potential electric vehicle drivers in Austria. Energy Policy 122, 701–714.

Ramaswami, A., Chavez, A., Ewing-Thiel, J., Reeve, K.E., 2011. Two approaches to greenhouse gas emissions foot-printing at the city scale. Environmental Science and Technology 45, 4205–4206.

RFF, 2019. Social cost of carbon 101. URL: https://www.rff.org/publications/explainers/social-cost-carbon-101/.

Rogelj, J., Elzen, M.D., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., Riahi, K., Meinshausen, M., 2016. Perspective : Paris Agreement climate proposals need boost to keep warming well below 2 C. Nature Climate Change 534, 631–639.

Rogers, E.M., 1962. Diffusion of Innovations. 1st ed., Free Press of Glencoe, New York.

Romer, P.M., 1990. Endogenous Technological Change. Journal of Political Economy 98, S71–S102.

Rosenzweig, C., Solecki, W., Hammer, S.A., Mehrotra, S., 2010. Cities lead the way in climate change action. Nature 467, 909–911.

Ryan, B., Gross, N.C., 1943. The Diffusion of Hybrid Seed Corn In Two Iowa Communities. Rural Sociology 8, 15–24.

Salmenkaita, J.P., Salo, A., 2002. Rationales for government intervention in the commercialization of new technologies. Technology Analysis & Strategic Management 14, 183–200.

Schleussner, C.F., Rogelj, J., Schaeffer, M., Lissner, T., Licker, R., Fischer, E.M., Knutti, R., Levermann, A., Frieler, K., Hare, W., 2016. Science and policy characteristics of the Paris Agreement temperature goal. Nature Climate Change 6, 827–835.

Schlomer, S., Bruckner, T., Fulton, L., Hertwich, E., McKinnon, A., Perczyk, D., Roy, J., Schaeffer, R., Sims, R., Smith, P., Wiser, R., 2014. Annex III: Technology-specific cost and performance parameters, in: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kreimann, B., Savolainen, J., Schlomer, S., von Stechow, C., Zwickel, T., Minx, J. (Eds.), Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 1329–1356.

Schroeder, A., Traber, T., 2012. The economics of fast charging infrastructure for electric vehicles. Energy Policy 43, 136–144.

Schumpeter, J., 1939. Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process. McGraw-Hill, New York.

Segerstrom, P.S., Zolnierek, J.M., 1999. The R&D Incentives of Industry Leaders. International Economic Review 40, 745–766.

Seto, K.C., Davis, S.J., Mitchell, R.B., Stokes, E.C., Unruh, G., Ürge-Vorsatz, D., 2016. Carbon Lock-In: Types, Causes, and Policy Implications. Annual Review of Environment and Resources 41, 425–452.

Sierzchula, W., Bakker, S., Maat, K., Van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68, 183–194.

Silvia, C., Krause, R.M., 2016. Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. Energy Policy 96, 105–118.

Smil, V., 2016. Examining energy transitions: A dozen insights based on performance. Energy Research and Social Science 22, 194–197.

Smith, J.E., Ulu, C., 2012. Technology adoption with uncertain future costs and quality. Operations Research 60, 262–274.

Smith, J.E., Ulu, C., 2017. Risk Aversion, Information Acquisition, and Technology Adoption. Operations Research 65, 1011–1028.

Solow, R.M., 1957. Technical Change and the Aggregate Production Function. The Review of Economics and Statistics 39, 312–320.

Sovacool, B.K., 2016. How long will it take? conceptualizing the temporal dynamics of energy transitions. Energy Research Social Science 13, 202–215.

SPEER, 2015. Incremental Demand Response Study: ERCOT Case Study.

Stiglitz, J.E., 2009. Regulation and failure, in: Moss, D.A., Cisternino, J.A. (Eds.), New perspectives on regulation. The Tobin Project, pp. 11–23.

Stone, B., Vargo, J., Habeeb, D., 2012. Managing climate change in cities: Will climate action plans work? Landscape and Urban Planning 107, 263–271.

Stoneman, P., 2002. The economics of technical diffusion / Paul Stoneman. Blackwell Publishers, Oxford.

Suri, T., 2011. Selection and Comparative Advantage in Technology Adoption. Econometrica 79, 159–209.

The City of New York, 2017. 1.5 °C: Aligning New York City with the Paris Climate Agreement. New York City Mayor's Office of Sustainability, New York.

Thengane, S.K., Hoadley, A., Bhattacharya, S., Mitra, S., Bandyopadhyay, S., 2014. Cost-benefit analysis of different hydrogen production technologies using AHP and Fuzzy AHP. International Journal of Hydrogen Energy 39, 15293–15306.

Thompson, P., 2000. Learning from the experience of others: Parameter uncertainty and economic growth in a model of creative destruction. Journal of Economic Dynamics & Control 24, 1285–1313.

Thompson, P., Waldo, D., 1994. Growth and trustified capitalism. Journal of Monetary Economics 34, 445–462.

Tishler, A., Milstein, I., 2009. R&D wars and the effects of innovation on the success and survivability of firms in oligopoly markets. International Journal of Industrial Organization 27, 519–531.

Tokyo Metropolitan Government, 2007. Tokyo Climate Change Strategy: A Basic Policy for the 10-Year Project for a Carbon-Minus Tokyo. Tokyo Metropolitan Government, Tokyo.

Tollefson, J., 2017. Trump says no to climate pact. Nature 546, 198.

TXDMV, 2017. County Vehicle Registration & License Transactions & Related Collections, CY 2015, Texas Department of Motor Vehicles.

TXDOT, 2016. Roadway Inventory Annual Data Tables, 2015-2016, Texas Department of Transportation.

Ulu, C., Smith, J.E., 2009. Uncertainty, Information Acquisition, and Technology Adoption. Operations Research 57, 740–752.

Unruh, G.C., 2000. Understanding Carbon Lock-In. Energy Policy 28, 817–830.

Unruh, G.C., 2002. Escaping carbon lock-in. Energy Policy 30, 317–325.

U.S. Census Bureau, 2016. Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2016.

U.S. Census Bureau, 2019. Quick facts: Population estimates. URL: https://www.census.gov/quickfacts/fact/table/US/PST045219.

van Benthem, A., Gillingham, K., Sweeney, J., 2008. Learning-by-Doing and the Optimal Solar Policy in California. The Energy Journal 29, 131–151.

Verdolini, E., Anadón, L.D., Baker, E., Bosetti, V., Reis, L.A., 2018. Future prospects for energy technologies: Insights from expert elicitations. Review of Environmental Economics and Policy 12, 133–153.

van der Vooren, A., Alkemade, F., Hekkert, M.P., 2012. Effective public resource allocation to escape lock-in: The case of infrastructure-dependent vehicle technologies. Environmental Innovation and Societal Transitions 2, 98–117.

Welsch, M., Deane, P., Howells, M., O Gallachóir, B., Rogan, F., Bazilian, M., Rogner, H.H., 2014. Incorporating flexibility requirements into long-term energy system models - A case study on high levels of renewable electricity penetration in Ireland. Applied Energy 135, 600–615.

Weyant, J.P., 2011. Accelerating the development and diffusion of new energy technologies: Beyond the "valley of death". Energy Economics , 674–682.

Wilkerson, J.T., Leibowicz, B.D., Turner, D.D., Weyant, J.P., 2015. Comparison of integrated assessment models: Carbon price impacts on U.S. energy. Energy Policy 76, 18–31.

Wolf, A., Seebauer, S., 2014. Technology adoption of electric bicycles: A survey among early adopters. Transportation Research Part A: Policy and Practice 69, 196–211.

Yeh, S., 2007. An empirical analysis on the adoption of alternative fuel vehicles: The case of natural gas vehicles. Energy Policy 35, 5865–5875.

Yu, J.J., Tang, C.S., Shen, Z.J.M., 2018. Improving consumer welfare and manufacturer profit via government subsidy programs: Subsidizing consumers or manufacturers? Manufacturing and Service Operations Management 20, 752–766.

Yu, Z., Li, S., Tong, L., 2016. Market dynamics and indirect network effects in electric vehicle diffusion. Transportation Research Part D: Transport and Environment 47, 336–356.

Zakeri, B., Syri, S., 2015. Electrical energy storage systems: A comparative life cycle cost analysis. Renewable and Sustainable Energy Reviews 42, 569–596.